Foreign Corporations and the Culture of Transparency: Evidence from Russian Administrative Data

Serguey Braguinsky, Sergey Mityakov [•]

Abstract

Foreign-owned firms from developed countries carry the culture of transparency in business transactions that is orthogonal to the culture of hiding and insider dealing in many developing and transition economies. In this paper, we document this using administrative data on reported earnings and market values of cars owned by workers employed in foreign-owned and domestic firms in Moscow, Russia. We examine whether closer ties to foreign corporations result in the diffusion of transparency to private Russian firms. We find that Russian firms initially founded in partnerships with foreign corporations are twice as transparent in reported earnings of their workers as other Russian firms, but they are still less than half as transparent as foreign firms themselves. We further find that increased links to foreign corporations, such as hiring more workers from them, raise the transparency of domestic firms. An important channel for this transmission appears to be "peer effects" or "benchmarking" with employees of domestic establishments experiencing higher gains in transparency when located closer to movers from foreign companies.

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[•] Braguinsky, Department of Social and Decision Sciences, Carnegie Mellon University, e-mail: sbrag@andrew.cmu.edu; Mityakov, John E. Walker Department of Economics, Clemson University, e-mail: smityak@clemson.edu. We thank Andrey Liscovich for outstanding research assistance. We are also grateful to Nicholas Bloom, Howard Bodenhorn, William Dougan, Ray Fisman, Francisco Perez Gonzales, Luigi Guiso, Steven Klepper, Tom Mroz, Anna Paulson, Andrei Shleifer, Kevin Tsui, Luigi Zingales, participants of NBER conference on "Causes and Consequences of Corporate Culture" for valuable comments and suggestions. All the remaining errors are our own.

I. Introduction.

The role of foreign capital in promoting economic transformation in developing countries and countries in transition has received a lot of attention in the literature. So far this attention, however, has almost entirely been limited to its role in the diffusion of knowledge (Branstetter [2006], Keller and Yeaple [2009]) and/or the transfer of more efficient managerial practices (Bloom et al. [2010, 2011], Görg et al. [2007], Sabirianova Peter et al. [2005]). Another and potentially even more important role of foreign capital is in creating and transmitting a culture of transparency in economic transactions.

Imagine being approached by someone who has an attractive mutually beneficial business proposal. The only problem is that the potential partner insists that everything is based on “a handshake,” with no formal written arrangements, money changing hands in cash, and no paper traces left of any transactions. If your economic culture is rooted in a Western-type economy you will probably walk away from such a proposal. But it is a natural way of doing business for economic agents whose culture is rooted in decades of hiding all that can be hidden from the government’s “grabbing hand” (Shleifer and Vishny [1998]).

The prevalence of this culture of hiding suggests that it is likely to be privately profitable given the institutional environment. But even though private benefits may outweigh private costs, hiding entails large efficiency costs for the market overall, such as market segmentation, high transaction costs outside a narrow range of trusted partners, and limited opportunities for outside investment (see, e.g., Shleifer and Vishny [1997], Braguinsky [1999], Braguinsky and Myerson [2007]). Hence, if the activity of multinational corporations can nudge the local corporate culture towards greater transparency, this would imply a major role of foreign capital in fostering economic efficiency in developing and transition countries.

We address this question by developing a novel way to measure transparency of earnings that is based on unique data available for Moscow, Russia’s political and economic center. The data contain information about officially reported earnings of Moscow residents together with the auto registration records that can be matched to earnings data for the same individuals over the period from 1999-2003. Reported earnings can be falsified, but it is virtually impossible to drive an unregistered car in Moscow. This difference is a key for defining our transparency measure, which is computed on the basis of discrepancy between observed car values for a given individual and his or her reported earnings.

The culture of hiding in which most Russian firms operate has been documented through survey data and anecdotal evidence in several past studies (e.g., Johnson et al. [2000], Yakovlev [2001]) as well as in our own recent study (Braguinsky, Mityakov, and Liscovich [2010], hereafter BML). We begin by documenting the higher transparency of wages and salaries paid by multinationals. We find that the employees' earnings reported by foreign-owned firms are on average four times higher than in domestic firms for the same car values, controlling for various other characteristics such as firm size, sector of economic activity as well as individual characteristics and time effects.

The finding that foreign-owned firms are more transparent in labor contracts than domestic companies has important implications in its own right. In particular, it suggests that conventional measures of the labor productivity gap between multinationals and local companies (which inevitably rely on reported output per worker or reported wages) should be taken with a grain of salt. Our results imply that a lion's share of actual employee compensation in domestic firms is paid outside of the formal reporting system ("black" as opposed to "white" wages, to use the term widely employed among Russian workers themselves).[1]

While the immediate role of multinationals in increasing labor productivity may thus be less than implied by conventional methodology, multinationals may nevertheless play an important (and so far understudied) role in improving the overall efficiency of the economy if they can spread the culture of transparency to domestic firms. We next use our data to examine whether links to multinationals do indeed have this effect.

We identify in the data private Russian companies with a non-zero fraction of workers with experience in multinationals (hereafter, "foreign-related firms," FRF). Our

[1] Such payments are often supplemented by employees stealing from the firms they work for; and the (net of costs) value of stolen goods, services and working time should be included in total employee compensation to make efficiency comparisons meaningful. Our methodology allows us to capture both of the above sources of unreported compensation. We benefited from discussions with Nicholas Bloom.

estimates, controlling for employer-individual-level fixed effects, indicate that the impact of hiring more workers from the multinationals on transparency of other workers in FRF is positive and significant both statistically and economically. An increase in the fraction of workers hired from multinationals by one standard deviation is associated with a 20 percent increase in transparency among workers who stayed employed in private domestic companies. Notably, we find no such effects for employees of state-owned establishments.

To better understand the mechanism that could account for these patterns, we collected the data on founding backgrounds and subsequent company histories for a large sample of FRF from their websites and other sources. One of the most striking findings is that Russian private firms that were founded in partnership with foreign-owned firms[2] offer about twice as transparent labor contracts as other FRF's, even when controlling for the fraction of workers with experience in multinationals. They thus locate almost exactly "in-between" the two opposite corporate cultures. Most of these firms are already owned entirely by Russian capital and are producing and selling their own products and services when our data coverage starts. Nevertheless, the high impact of "cultural influence" from multinationals experienced at the time of founding is clearly detectable in the data.

Apart from direct influence as in cases above, we looked for a mechanism that could make domestic companies more transparent when they increase hiring from multinationals. One possible channel is "vertical spillovers," where business practices of companies change with changes in top managerial personnel (e.g., Bertrand and Schoar [2003]). This conjecture led us to look for changes in transparency that might be driven by hiring high-ranking employees and managers from foreign-owned firms but we did not find much empirical support for this hypothesis.

Instead, we find empirical patterns that indicate the "horizontal" nature of transparency spillovers, that is, among employees who are closer to newly hired workers from multinationals in the job quality space. We speculate that this might reflect peer effects. It may also be the case that to prevent disruption in the workplace, domestic firms are forced to engage in "benchmarking" behavior, that is, bringing the officially reported

[2] Such as joint ventures with foreign investors holding a minority share, or authorized distributors of foreign producers.

earnings of incumbent employees closer to the earnings they have to officially pay to workers recruited from multinationals. We also look at the multinationals' countries of origin and, not surprisingly, find that spillovers of transparency are more strongly pronounced when the new hires come from firms originating in countries with better institutional structure.

Our paper is related to several strands in the literature. The development economics literature investigates the impact of foreign direct investment on economic performance of companies in recipient countries. Existing attempts to assess this impact generated mixed results: Aitken and Harrison [1999] and Smarzynska [2004] present evidence of positive spillovers from foreign firms presence in the industry, while Aitken, Harrison, and Lipsey [1996] find no or even negative effects. More recently, availability of employee-employer matched studies allows for more detailed analysis through the channel of labor mobility; see, e.g., Görg and Strobl [2005], and Balsvik [2011].

Our paper follows this empirical approach. However, our conceptual focus is complementary to the existing literature. Rather than trying to estimate actual productivity gains from the presence of multinationals in the industry, we focus on the latter's role in spreading the corporate culture of transparency, affecting the hidden component of earnings. We argue that without distinguishing between reported vs. true earnings comparing wages in domestic and foreign firms is likely to be misleading.

Our paper also contributes to the growing literature on the shadow or hidden economies (see Schneider and Enste [2000] for a survey). Most of the studies in this field rely on indirect aggregate indicators like electricity consumption (Alexeev and Pyle [2003]), share of cash in transactions (Tanzi [1983]), or on survey data with self-reported consumption and incomes (Pissarides and Weber [1989], Gorodnichenko et al [2009]).[3] Our approach employing administrative data allows us to obtain more precise and disaggregated estimates of hiding and its determinants.

In Section II we present an overview of the system of hidden earnings in the Russian economy and briefly discuss some of the previous findings. Section III describes the data and the construction of our sample. It also lays out the empirical estimation model. Section IV presents empirical findings concerning the relative transparency of

[3] See Hanlon et al. [2007] and DeBacker et al. [2011] for notable exceptions.

multinationals and domestic Russian firms and how ties to multinationals affect the transparency of domestic firms. It also examines possible mechanisms for these effects. Section V contains extensions and robustness checks. Section VI concludes.

II. Hidden Earnings and Multinationals: an Overview

Most hidden earnings in Russian companies appear to be "black wages," which are either envelopes with cash handed to workers by the management or more elaborate schemes, where compensation is disguised as, for instance, an insurance policy or a foreign exchange transaction on which the employer deliberately takes a loss.[4] Of course, the schemes are arranged in such ways that they do not inflate firms profits either. Indeed firm-level surveys have produced evidence of almost perfect correlation between the presence of hidden wages and hidden sales and profits (Johnson et al. [2000]). Firms benefit because they evade the payroll tax, as well as the sales tax (in case of unregistered cash transactions) or the profit tax (when "black wages" are disguised as losses on investment). Importantly, "black" wages are used by management to circumvent labor regulations and reward or punish employees with impunity. The system of "black wages" is thus part of the peculiar culture of cronyism in the workplace, arguably inherited from the final decades of the decaying planned economy.

An important part of hidden earnings appears to be comprised of employer-tolerated theft. The Soviet Union under Stalin would put in front of the firing squad an individual who stole just a handful of crop from the "collective" field. In the Soviet Union during its final years, the "parallel economy" dealers were stealing with impunity whole cargo trains, supposedly monitored at the *Politburo* level (Vaksberg [1992], Braguinsky and Yavlilnsky [2000]), and ordinary workers were not far behind. A bartender would steal liquor, a butcher would steal meat, and so forth. The culture of stealing was not limited to the trade and services sector (although it was certainly relatively more prevalent there) but was also common in manufacturing firms (where

[4] Even a casual web search comes up with at least a dozen sites that openly discuss the costs and benefits of "white" versus "black" wages from the employers' and employees' perspective, compare various schemes employed by firms, etc., e.g., http://mirsovetov.ru/a/miscellaneous/employment/salary-black-white.html, http://trudprava.ru/index.php?id=1423. For a good source in English see Yakovlev [2001]. See also BML, Appendix 8.

employees would steal raw materials or use their workplaces for side jobs), transportation services (where a taxi driver would take a client without turning on the meter), and so on.

This culture of stealing carried over to the post-communist economy where many new owners, even in genuinely private firms, were by and large either incapable or unwilling to change it. Instead, the value of stolen goods, utilities and time at work is implicitly included in labor contracts, thus reducing the official compensation firms pay to their employees. And, just as with “black wages,” employer-tolerated theft also gives a lot of discretionary powers to managers over their workers (you behave and I will look the other way, you don't behave and I will have you arrested and prosecuted).[5]

Even though the system of “black wages” (explicit or implicit) as described above is inefficient from the economic welfare point view, it does convey some private benefits also to workers, at least to those who play by the prevailing rules, making it particularly hard to dislodge once firmly entrenched. A worker accepting a non-transparent labor contract with a large “black” component or implicitly tolerated workplace theft saves on the personal income tax and also on the part of the payroll tax that would otherwise be shifted to wages. Just as in “corruption with theft” (Shleifer and Vishny [1993]) the system aligns the interests of the worker and the employer, with the loser being the state (and overall economic efficiency). The individual costs of “black wages,” on the other hand, at least in an environment where this culture is well entrenched and the risk of prosecution is low, are mostly of a moral or psychological nature, and are going to be especially high for those who want to be law-abiding citizens or for those who have low tolerance for arbitrary behavior by the management.[6]

There are reasons to believe that the corporate culture brought into Russia by foreign capital would be different. First, foreign-owned firms come from an environment where transparent labor contracts are the norm and “black wages” are generally balked at by both employers and employees. In addition, managers of multinational corporations

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[5] While many explanations have been advanced for the fate suffered by the former richest man in Russia (in jail since 2003), we find the explanation along the lines above to be the most likely one. The person in question might have well been guilty of at least some of the theft and tax evasion charges he was convicted on, but so were many other “oligarchs” who did not suffer his fate. The difference seems to be that he did not “behave.” Thus the culture we are talking about here does indeed seem to pervade the whole social contract, from the very top to the very bottom.

[6] There is also the cost of forgoing employers’ contributions to the social security fund, which will be felt more by older workers who are closer to retirement.

are less likely to tolerate employee theft. In efficient labor markets, this means that the "white wages" they have to pay to their employees have to be higher than the "white" component of wages paid by their domestic counterparts.

It should be noted that higher transparency of foreign-owned firms does not have to be rooted in some particularly different "culture." All our analysis below goes through if we assume that it is simply too costly or too risky for foreign-owned firms to try to play by the same rules as domestic firms. Foreign-owned firms, especially large multinational corporations, must be conscious of their reputation, both in their home countries and world-wide. They can also be subject to litigation and punitive sanctions in their home countries for breaking the laws in other countries and they commonly lack the necessary connections to escape the scrutiny of the Russian tax authorities.

Whether for cultural reasons or otherwise, the presence of multinationals expands the menu of choices available to workers in the domestic economy. In the absence of an alternative system, there might be no chance for workers whose personal costs of non-transparent labor contracts are high to change the environment without suffering serious economic penalties. For example, refusing to accept "black cash" will result not only in forgoing a large part of the actual compensation but may very well result in losing the job itself, and the same is true about refusing to steal while working for an employer where everybody else is stealing. To put it simply, the presence of honest people is considered to be a danger to their peers in the environment characterized by cheating and stealing.

If, however, foreign-owned firms simply offer a more palatable type of employment to workers with intrinsic preferences for transparency, their role in changing the overall corporate culture in the recipient economy will be limited. Multinationals would end up being small islands of greater transparency (and potentially greater efficiency) amidst the sea of other firms with low efficiency and widespread "black wages." The presence of such islands will not make much of a difference in how the majority of the domestic workforce goes about doing their business. After all, the fraction of genuinely foreign-owned firms in total employment in our Moscow data is less than 2 percent. To have a real impact on the recipient economy as a whole, higher transparency of multinationals should be somehow transmitted to domestic firms. Of course, the same is also true of technology diffusion and the spread of better management practices.

It turns out from our analyses below that not only are the multinationals indeed much more transparent in setting their wages, but also that closer ties to them (such as working with foreign capital at the time the firm was founded, or increasing the number of workers hired from multinationals) positively affect the transparency of domestic firms that enter into such relations. This provides some hope that more penetration of foreign capital and closer links between foreign-owned and domestic businesses over time could change the overall situation for the better.

III. Data and Empirical Methodology

3.1. Data Sources and Sample Construction

Our data come from two main sources. The first is five administrative databases of reported incomes between 1999 and 2003. The databases, which contain information allowing us to identify both income sources (employers) and income recipients (individuals), are official records of all payments and taxes generated by all income sources registered in Moscow.[7] As is usual with administrative data, parts of the data were of poor quality and had to be eliminated. Specifically, we eliminated cases where individuals' names contained abbreviations, obvious typos or non-alphabetic characters, and those without information on dates of birth or addresses. Since our purpose in this paper is to analyze the impact of foreign multinationals on the transparency of income reporting by the domestic workforce, we only use the data on Russian nationals.[8] We also dropped all observations on individuals who appeared to be present more than once in the income database in a given year. Random testing revealed that in about 10 percent of such cases, the second, third and so on entries were exact duplicates of the first one (sometimes with a trivial correction of a typo), so including those would have resulted in counting incomes of such individuals more than once. This procedure also eliminated individuals with multiple income sources in a given year, which could have complicated the interpretation of our estimates as explained below.

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[7] These databases stripped of all individual identifying information have been also employed in a few previous studies (see Guriev and Rachinsky [2006], Braguinsky [2009], Braguinsky et al. [2010]).

[8] In addition, foreign nationals working for multinationals or even private Russian firms often receive a large part of their compensation in their home countries, making their officially reported earnings in Moscow all but useless for our purposes.

After eliminating the cases discussed above we are left with 26,889,790 observations (4,329,337 in 1999, 5,790,422 in 2000, 5,946,298 in 2001, 4,592,606 in 2002 and 6,231,127 in 2003). This corresponds to about 60 percent of all raw entries contained in the five databases. We then used individual-identifying information contained in the data to match the same individuals across income databases in different years. We were able to match 19,201,689 observations as related to the same individual in at least two different years. For the remaining 7,688,101 observations (about 29 percent of the total) we were not able to obtain repeated observations in different years, so we treat them as separate individuals present in the income databases in only one year and employ them for cross-section analyses only. Appendix 1 explains the steps used in the matching procedure and also provides more details about the number of individuals matched across various years.

Our second data source is the 2005 auto registration database, which contains full vehicle histories, including retrospective data on past owners. We used the vehicle identification number (VIN) to trace its history of owners. We eliminated all vehicles owned not by individuals, as well as trucks, mini-buses, motorcycles and other non-passenger cars (even if registered in the names of individual owners). We then used the information about the make, model and year to impute the market value of the car in a given year according to a standardized procedure, described in Appendix 2.

Individual identifying information contained in the auto registration database was used to match car owners to their income and tax records in the income databases described above. We were able to match 2,913,359 individuals who owned at least one car in 2005 to their corresponding entries in at least one of the income databases above. 693,366 (23.8 percent) of them owned cars with missing information about the vehicle's VIN, making it impossible to trace their history of ownership. We elected to eliminate such car owners as well as all cars with missing VINs from our analysis.[9] In our main analysis, we also dropped the bottom 20 percent of observations with the lowest market value of the cars (about $1,200 or less) out of concern that such old and highly

[9] Since most of the cars with missing VINs are old and largely depreciated, the total estimated value of cars in our sample drops by less that 14 percent as a result of eliminating cars with bad VINs. We also confirmed that retaining those cars and their owners does not affect any of the results presented below, in fact estimated effects were even larger without dropping those observations.

depreciated cars could not serve as a proxy for true earnings for the period in our data. We conducted robustness checks that did not impose this cutoff or imposed some other reasonable cutoffs and the estimation results were similar.

To address the issues of corporate culture we needed to classify employers by ownership and sector of activity. We elected to exclude self-employed individuals because income reporting by the self employed has been identified as problematic even in advanced market economies (e.g., Hamilton [2000]). The total number of Moscow legal entities in our sample containing matched car ownership-incomes data is 190,965. Unfortunately, we could not rely on an automated procedure to assign ownership and sector to most of them. One especially serious problem from the perspective of this study is that many firms that are officially registered as foreign-owned are actually firms owned by Russian capital through paper offshore companies. These needed to be separated from legitimate foreign-owned firms, and the only way to do it was to examine each potential foreign-owned entity manually. Furthermore, it is well known that a large number of firms registered in Moscow are paper companies created (and dissolved shortly after) for the sole purpose of money laundering.[10] If too many of those paper companies found their way into our sample, any comparisons between the transparency of multinationals and Russian firms could be seriously compromised.

We therefore start our analysis with 13,263 income-generating employers (legal entities) that we had already classified for our previous study (BML), in which we used a random sample of car owners actually residing and legitimately employed in Moscow for all five years 1999-2003. We used employer identification numbers and names and addresses contained in the income databases to retrieve information from open sources about ownership and the sector of economic activity of all those employers.

Our classification procedure identified 10,203 out of 13,263 employers to be private, non-foreign firms, 2,793 to be government agencies or state-owned firms, and 257 to be genuine (not offshore-type) foreign-owned firms. Given that our focus in the current paper is on investigating possible corporate culture spillovers between foreign-owned firms and Russian firms related to them, we decided to add more firms that would

[10] An official for the Russian Federal Tax Service estimated that 2 out of 5 firms registered in Moscow were such "one-day" entities, as they are called in Russia – see http://www.delpartner.ru/?act=n&id=33.

be hiring workers with experience in multinationals. For this purpose, we traced the movements of individuals who worked for the 257 foreign-owned employers classified in the previous stage, and obtained information about ownership and sector of economic activity for all their other employers over the five observation years. This resulted in adding 1,137 more employers, 677 of them Russian private firms, 179 government agencies and state-owned firms and 281 foreign-owned firms. In the process we also collected some additional information about those "foreign-related" firms which will be used below. In the end, the total number of distinct employers for which we have information about ownership and sector of economic activity is 14,400, 10,890 of them private Russian firms, 2,972 government agencies/state-owned firms and 538 foreign-owned firms. See Appendix 3 for the details of the breakdown of the data by sectors of economic activity.

The number of observations where individuals received incomes from these 14,400 employers amounts to roughly half of all observations in the data (13.6 million out of 26.9 million of all observations in the five income databases and 1,074,247 out of 2,219,933 among matched observations across income and car ownership databases). Thus, even though the number of employers for which we have information about ownership and sector of activity is relatively small (just about 7 percent of all officially registered legal entities present in all five income databases), we in fact have observations on 50 percent or more of all legitimate (that is not paper) companies in Moscow in terms of employment. Notably, more than 70 percent of employers used in this paper are present in all five income databases, while less than 10 percent show up in just one year (which in general might be a tell-tell sign of a paper company).[11] Appendix 3 contains more comparisons between employers used in our analyses and the rest of Moscow legal entities and discusses the representativeness of our data.

Even though we are thus reasonably confident that the remaining data include for most part legitimate companies and sources of income, in the statistical analyses below we take some extra steps to eliminate potential problems from including car owners with income sources unrelated to legitimate employment. First, we exclude observations on

[11] We checked the robustness of all the estimation results below to excluding employers with presence in only one database and confirmed that they remain qualitatively the same.

earnings that were below the official minimum wage in any given year (5-7 percent of observations, depending on the year). We also exclude car owners whose reported earnings exceeded the equivalent of $100,000 in any given year (less than 0.3 percent of observations) out of concern that the link between earnings and car values may be problematic in such cases. Second, we examined sources of income of car owners in our sample and identified and eliminated individuals whose sole source of income appeared to be not from employment (lottery winnings, interest and dividend payments, insurance payments, research grants, etc.). Third, we excluded individuals younger than 18 and older than 60, which is the retirement age for males in Russia (for females it is even lower at 55). Our sense is that in the vast majority of the remaining cases we are looking at "serious" car owners whose main source of income is legitimate employment (even though possibly with a large fraction of "black wages"). We also conducted robustness checks where we did not impose any of the above restrictions on the sample and confirmed that the results were qualitatively the same.

3.2. Summary Statistics

The total number of observations used in our main analysis is 391,052. Of these, 187,326 observations are generated in the private, non-foreign owned firms, 188,679 observations are generated in government employment (including government services, such as law enforcement, education, health care, etc.) and state-owned firms, and 15,047 observations are generated in (legitimate) foreign-owned companies. For each year, we also calculated the percentile of an individual in our sample in the overall earnings distribution of his or her employer (which captures the relative position of the individual in the employer's hierarchy) and the size of the employer by counting the total number of entries pertaining to its identification number. All ruble values were converted to US dollars using average market exchange rates for each year and the dollar values were adjusted to 1999 dollars using the Bureau of Labor Statistics Consumer Price Index.

The top panel of Table 1 presents summary statistics for three types of ownership; private domestic firms, government employment and state-owned enterprises, and foreign-owned firms. The bottom panel presents a further breakdown among private domestic firms; the first column includes car owners in firms with no workers for whom we observe past experience working for a foreign-owned firm (non-foreign-related firms, non-FRF), the second column presents the data on foreign-related firms (FRF) i.e. the firms with non-zero fraction of workers with work experience in foreign-owned firms, while the third column limits the sample in the second column to the top 10 percent of FRF with the highest fraction of workers with work experience in foreign-owned firms (which corresponds to this fraction being greater than or equal to about 1 percent of their total employment).

Several features of the data immediately attract attention. First, looking at car values in the top panel of Table 1, employees in foreign-owned firms have on average 6.2 percent more expensive cars than employees in private Russian firms. But comparing the corresponding numbers for reported earnings, those in foreign-owned firms exceed those in private Russian firms on average by more than 320 percent. The picture is similar when comparing employees of foreign-owned firms to employees in government agencies and state-owned enterprises, except that both car values and reported earnings are lower in government employment than in the private sector. As a result of this, the simple mean ratio of car values to income is about 75 percent lower in foreign-owned firms compared to other employers. Mean car values are almost double the mean amount of annual earnings among car owners employed in the private sector and more than double in government/state-owned sector, which makes them look unrealistically high.

Consequently, if one were to do labor productivity comparisons between multinationals and private Russian firms on the basis of reported earnings in Table 1, one would inevitably conclude that foreign-owned companies were on average 4.2 times more productive. However, looking at car values, one cannot but suspect, even from these most basic summary statistics, that most of this observed differential is actually due to differences in transparency (a high fraction of “black wages” among non-multinationals).

The evidence presented in the bottom panel of Table 1 reveals sharp differences in car values to reported earnings ratios also between FRF and non-FRF. Car values of workers in FRF are about the same as those of workers in non-FRF, but their reported earnings are 76 percent higher. Car owners working for FRF in the top decile as measured by the fraction of workers with experience in foreign-owned firms (see Section

4.2.2 below for the details about how this fraction was constructed) have sharply higher both car values and reported earnings than the rest of the private domestic firms. We will come back to this issue below.

Comparing demographics, car owners in foreign-owned firms are about 4.5 years younger than those in Russian private firms and about 6 years younger than in government employment. Car owners in foreign-owned firms are also more likely to be female. The percentiles in the overall earnings distribution of employers, on the other hand, are very similar and much above the median, indicating, not surprisingly, that car owners are overall more productive workers in their respective employers. Also, the average size of multinationals in Moscow is relatively small, about 40 percent of the average size of private firms and just 8 percent the size of government agencies/state-owned enterprises. The fraction of car owners among multinationals' employees is, on the other hand, twice as high as in government employment and about 40 percent higher than in private Russian firms, indicating (once again not surprisingly) that multinationals on average hire workers of higher productivity. Higher fraction of car owners among employees of foreign-owned firms may also be due to a more equal distribution of earnings – as can be seen from Table 1, the coefficient of variation (the ratio of the standard deviation to the mean) of car values in this category is the lowest in Table 1 and the same is true of the corresponding Gini coefficients (not shown). Also, the top decile of FRF in the bottom panel of Table 1 looks very similar to foreign-owned firms in terms of its demographics, the fraction of car owners among all employees and the coefficient of variation of car values.

It thus appears from the examination of the raw data that (a) foreign-owned firms are more transparent in how they report earnings of their employees as compared to both private Russian firms and government employment, and (b) foreign-related firms, especially those of them that hire relatively more workers from multinationals are positioned somewhere in-between the multinationals and non-foreign-related private domestic firms in terms of transparency. The data in Table 1 also indicate that, contrary to some common perceptions, both reported and true earnings (as proxied by car values) are distributed more evenly among employees of foreign-owned firms and foreign-related firms than among employees of other private Russian domestic firms. In the next section we will put these conjectures from the raw data to test using regression analyses. We begin by specifying our empirical estimation model in the next subsection.

3.3. Estimation Model

As already mentioned, our approach starts from the observation that it is relatively easy to misreport earnings, but it is costly to drive an unregistered vehicle.[12] This difference is the key to our identification strategy, which employs matched administrative data on wages and car values to measure hidden earnings. Specifically, we assume that employers pay a certain fraction of true economic earnings of their employees in "black wages," either explicitly (in envelopes) or implicitly (as in cases of employee theft or side jobs using workplace facilities and working time).

Specifically, let employee *i*'s earnings at time *t* working in firm *j* be reported in the amount of $E_{i,t}^{R} = \Gamma_{i,j(i),t} E*_{i,t}$, where $E*_{i,t}$ are true economic earnings and $\Gamma_{i,j(i),t}$ is the fraction reported. This fraction will likely depend on employer characteristics $\mathbf{S}_{j,t}$, such as ownership, sector of activity, firm size, etc. This vector **S** will also include measures for amount of workers hired from foreign-owned companies to capture the effect of labor exchange with multinationals.

The fraction $\Gamma_{i,j(i),t}$ may also depend on a range of individual-specific characteristics $\mathbf{X}_{i,t}^{(1)}$, such as age, gender, position in the firm's hierarchy and so on. Finally, there might be time effects in reported earnings caused, for example, by institutional changes. Thus, we consider the following specification for reported earnings:

$$\ln E_{i,t}^{R} = \ln E*_{i,t} + \mathbf{b}'\mathbf{S}_{j(i),t} + \mathbf{g}_1'\mathbf{X}_{i,t}^{(1)} + \phi_1(t) + \eta_{i,t}, \qquad (1)$$

Coefficients **b** are the main focus of our analysis as they measure average income hiding associated with different characteristics of employers **S**. The more negative the particular coefficient β_k, the larger the fraction of hidden earnings in total economic earnings among individuals employed in the category of employers possessing characteristic *k* and vice versa. Our identifying assumption is that while the fraction of reported income could depend **S**, the demand for the stock of cars has the same

[12] Moscow police routinely conduct traffic stops to check the paperwork. Unregistered vehicles may be impounded and can be recovered only after paying a fine and producing the registration document.

(controlling for individual-specific characteristics) functional form in all sectors. Specifically, we consider the following car stock demand equation:

$$\ln C_{i,t} = \lambda \ln E^*_{i,t} + \mathbf{g}_2' \mathbf{X}_{i,t}^{(2)} + \phi_2(t) + u_{i,t} \tag{2}$$

That is, the demand for the stock of cars depends on actual earnings $E^*_{i,t}$, individual characteristics $\mathbf{X}_{i,t}^{(2)}$, time effects $\phi_2(t)$, and an individual and time specific disturbance term $u_{i,t}$.

In order to estimate coefficients **b** associated with particular employer characteristics **S**, we use equation (2) to substitute for unobserved actual economic earnings $E^*_{i,t}$:

$$\ln E_{i,t}^R = \frac{1}{\lambda} \ln C_{i,t} + \mathbf{b}' \mathbf{S}_{j(i),t} + \mathbf{g}' \mathbf{X}_{i,t} + \phi(t) + \varepsilon_{i,t} \tag{3}$$

where $\mathbf{g} = \mathbf{g}_1 - \frac{1}{\lambda}\mathbf{g}_2$, $\phi(t) = \phi_1(t) - \frac{1}{\lambda}\phi_2(t)$, and $\varepsilon_{i,t} = \eta_{i,t} - \frac{1}{\lambda}u_{i,t}$. Unfortunately, in general estimation of equation (3) is likely to produce biased estimates of **b** since car values are correlated with part of the error term. However, if the value of income elasticity of demand is known, we can estimate the relative (non)transparency of earnings associated with employer characteristics **S** by using the following regression equation:

$$\ln E_{i,t}^R - \frac{1}{\lambda} \ln C_{i,t} = \mathbf{b}' \mathbf{S}_{j(i),t} + \mathbf{g}' \mathbf{X}_{i,t} + \phi(t) + \varepsilon_{i,t}. \tag{4}$$

In the empirical analysis below we employ the value of λ=0.35 as estimated in BML using a sample of employees of foreign corporations where we have reasons to believe that they reported wages and salaries of their employees truthfully.[13] The estimation results are robust to reasonable variations in the value of λ and also to assuming an elasticity that varies with income (see Section 4.3 and Table 8 below).

[13] The value of λ=0.35 is also very close to estimates obtained from similar NLSY data, where income underreporting is presumably a non-issue. See BML, Appendix 4 and 5 for details.

IV. Results

4.1. How Much More Transparent Are Multinationals?

To evaluate exactly how much more transparent foreign corporation are in their labor contracts using our empirical estimation model, Table 2 presents the results of estimating regression (4) in pooled OLS, median regression, and individual fixed-effects specifications. We include percentile in the earnings distribution of the employer in both specifications, as well as age and a male dummy in the pooled OLS specification. Both specifications also include observation year dummies (with the omitted year dummy being 1999).

Our main variable of interest is the dummy equal to 1 if the company was foreign-owned and 0 otherwise. We also include a dummy equal to 1 if the employer was a government entity or a state-owned enterprise and zero otherwise. Since other employer characteristics such as firm size and sector of economic activity may also affect the fraction of economic earnings paid to employees in the form of "black wages," we include the (log of) the number of employees as well as 17 industry/sector dummies as controls, although to save space we report only a few coefficients on select sector dummies in Table 2 (see Appendix 3 for the details of sectors of economic activity classification and the distribution of those sectors in our sample).

The coefficient on the foreign ownership dummy is estimated to be 1.656 in the pooled OLS specification and 1.132 when controlling for individual fixed effects. The effect has high economic importance; in the OLS specification, other things equal, foreign-owned firms are estimated to report on average more than 4 times (exp(1.656) – 1 = 4.238) higher earnings paid to their employees with the same car values than private Russian firms. In the fixed-effect specification the effect is smaller but still very large. The higher transparency of foreign-owned firms comes as no surprise, of course, as it can be seen in the raw data in Table 1. The regression estimates in Table 2 are also consistent with the BML estimates employing a smaller representative sample of car owners with observations on non-zero earnings and car values in all 5 years.[14] The estimated

[14] The coefficients on foreign ownership dummy in cross-section and fixed-effect estimations in BML were 1.487 and 1.016, respectively, on 15,492 observations.

coefficients in the median regression are very similar to those obtained from the OLS specification. Thus, the differences we find between foreign-owned firms and other employers are not driven by higher earnings inequality in foreign-owned firms (which, as already noted above, actually appear to have more equal earnings distribution, both true and reported, than do domestic firms).

Among other variables, firm size has a statistically and economically highly significant effect on the transparency of reported earnings; labor-intensive sectors such as trade and services as well as sectors with a lot of opportunities to hide earnings, such as banking and finance, are relatively less transparent than manufacturing, utilities and IT and communications (which is the omitted sector in Table 2).[15] There is also an overall trend towards more transparency of reporting over time, especially pronounced between 2000-2002, which coincides with the major tax reform that reduced the burden of both personal income tax and the payroll tax (Gorodnichenko et al. [2009]). Finally, age has a positive effect on transparency (presumably because older individuals are closer to retirement age and are thus more concerned about losing employers' contributions to their pension fund, which is only paid out of the "white" part of the wages). An individual's position in the employer's hierarchy (measured by his or her percentile in the earnings distribution of their employer) also has a positive effect on transparency. Because we discussed all these findings in detail in our previous study, we do not repeat this discussion here but we will continue to use firm size, sector of activity and other employer and individual characteristics as controls whenever appropriate.

4.2. Multinationals' Culture of Transparency and Domestic Firms

Reducing the unreported ("black") component of wages and salaries is an important step toward improved efficiency of economic transactions (to say nothing of government tax revenues). Hence, the question whether the culture of higher transparency exhibited by foreign corporations spreads to domestic firms is of first-order importance. In this section, we focus our attention on how economic ties to

[15] It is interesting to note that the magnitude of estimated underreporting in smaller firms as compared to larger firms completely reverses the conventional wage-size effect, which has been found to hold also in Russia in survey data (Idson [2000]). See the discussion in BML for more details.

multinationals affect the transparency of domestic private firms. We also compare them to the effects on "black wages" in government employment.

4.2.1. Evidence From Firms' Historical Backgrounds

As already mentioned, we have assigned ownership and sector of economic activity to 14,400 employers. To obtain more details about how the firms were founded (and when), we went to these firms' websites and other open sources for company histories. As a result of this, we have been able to obtain additional information on 1,378 privately owned Russian firms about the background of their founding. In particular, we learned whether foreign partners were involved from the outset (such as a firm being founded as a joint venture with foreign investors holding a minority share, or an authorized distributor of a branded foreign product, etc.). These 1,378 employers cover about 37 percent of all car owners employed in the Russian private sector in our data. We were also able to identify the year the firm was founded for 868 of those firms.

Among the 1,378 private Russian firms with known history, foreign partners were involved in founding 103, with about 9,346 observations on car owners in our sample. For 86 out of those 103 firms we were able to determine the year of founding, and in two thirds of the cases (and 83 percent of observations on car owners) the founding year goes back to the last years of communism or the very first few years of the transition to a market economy (1988-1994). It also turned out that most of these firms had long outgrown the initial circumstances surrounding their founding – the Russian owners often bought out foreign partners in former joint ventures or former distributors of foreign products long ago started their own production lines. Thus, any difference in the culture of these firms and other firms during the period of our observation can indeed be traced to historical circumstances surrounding their founding.

In Table 3 we present the results of estimating the regression similar to (4), using observations on car owners in private domestic companies for which we know the circumstances of their founding. We exclude observations on workers who themselves had work experience in multinationals, so all the results pertain to employees of foreign-related companies who themselves were not observed working in foreign-owned firms at any point in our data. The variable of interest is the dummy equal to 1 if the firm was founded in partnership with foreign capital and zero otherwise but all other controls mentioned in Table 2 are also included, although to save on space we only report the coefficient on firm size. Since firm age and, more generally, the year the company was founded may also affect transparency, in the estimation results presented in column (2) we control for this non-parametrically by including 16 founding year dummies (from 1988 to 2003). This also reduces the sample size as we were not able to identify founding dates for about half of the employers used in this estimation. Columns (3) and (4) present estimation results in the same specifications as in columns (1) and (2), respectively, using the median regression.

The magnitude of the coefficient on the foreign partner at founding dummy in (1) suggests that being founded in partnership with foreign capital increases the transparency of a Russian domestic company on average by more than 50 percent. Adding founding year dummies reduces this coefficient just marginally although it is less precisely estimated, but overall the results are very similar and median regression estimates also produce similar results. Thus, interaction with the corporate culture of multinationals during early years of operation makes Russian private companies considerably more transparent than their peers.

4.2.2. Cross-Section Estimates

Is the influence of foreign capital limited to the founding process or does it have an effect on a wider set of domestic establishments through day-to-day interaction of employees? Here we consider one potential channel of such interaction: labor mobility. We hypothesize that as employees move from foreign corporations they might bring more transparency to the absorbing domestic companies.

To obtain a measure of labor mobility intensity from multinationals, we used all 13,599,649 observations on the 14,400 income-generating employers for which we had assigned ownership (see Section III above) and recorded all moves by income recipients (not necessarily car owners) from foreign-owned firms to non-foreign owned firms and entities in all years covered by our data (1999-2003). Anyone who moved from a foreign-owned firm to a domestic entity was "labeled" appropriately. We then computed the ratio of the number of such workers to the total number of individuals employed in any given domestic firm or government entity for each year. This ratio gives us the firm-year specific fraction of workers with observed prior experience of working for foreign-owned firms in the total number of workers in a domestic firm, which we will call "fraction of workers with multinational experience," or "multinational fraction" for short.

Since our data window is limited to five years (1999-2003), the multinational fraction is by construction zero for all domestic firms in 1999. Thus, unless the firm itself was founded in 2000 or later, we cannot meaningfully use the absolute magnitude of this fraction in our econometric analysis. We can, however, use changes in the fraction of workers with experience in foreign-owned firms over time and estimate its effect on the increase in transparency of reported earnings by domestic firms experiencing such an increase, while controlling for employer (and individual) fixed effects. The results of this analysis are presented in subsection 4.2.3 below.

In this subsection we utilize the limited number of observations on firms where we know the date of founding was between 2000 and 2003 to see how the multinational fraction (which in this case is equal the actual fraction of workers with prior work experience in foreign sector) affects transparency of income reporting for employees who themselves did not come from multinationals in the cross section of domestic companies. More specifically, we estimate the following equation:

$$\ln E_{i,t}^{R} - \frac{1}{\lambda}\ln C_{i,t} = \alpha FF_{j(i),t} + \mathbf{b}'\mathbf{S}_{j(i),t} + \mathbf{g}'\mathbf{X}_{i,t} + \phi(t) + \varepsilon_{i,t} \qquad (5)$$

where $FF_{j(i),t}$ is the (log of) multinational fraction. We also include time fixed-effects and time-varying individual-level controls (percentile in the employer earning distribution and, in the first difference specifications (3) and (6), also the dummy for male gender), as well as the usual firm level covariates (log of the number of employees and 17 industry/sector dummies). We restrict the sample to employees who themselves did not previously work in foreign sector and continued to be employed with the same domestic employer. The coefficient on multinational fraction thus shows how transparency of "stayers" in domestic companies differs depending on the number of people with prior work experience in the foreign sector hired by a given employer.

Table 4 presents estimation results where we look at the effects of any hires from multinationals (captured by the dummy equal to one if a firm had a non-zero multinational fraction and zero otherwise) and at the effects of higher multinational fraction among those firms that do higher from multinationals. All specifications include all the controls reported in Table 2, along with 4 dummies for different years the companies were founded (between 2000 and 2003).

The first two columns show that the effect of hiring from foreign-owned firms (versus not hiring at all) is positive and quite large, although standard errors are high so that the coefficients are not very precisely estimated. We suspect that one reason for this may be a small sample size of firms that did not hire from multinationals; an inspection of the data reveals that about 70 percent of private Russian firms founded between 2000 and 2003 did actually hire at least one worker from a foreign-owned firm over those years. This fact that is quite interesting by itself. In column (3) of Table 4 we limit the sample to only those firms that did hire from multinationals and estimate the effect of the size of the multinational fraction on transparency. The coefficient on the (log of) the fraction of employees that came to private domestic firms from foreign-owned firms is indicates that a 10 percent increase in this fraction is associated with 8 percent increase in our measure of transparency, statistically highly significant. The results obtained by estimating a corresponding median regression (not shown) were also similar. We conclude that close ties to foreign capital, including hiring from multinationals at early stages of company existence, have a sizable effect on transparency.

4.2.3. Fixed Effects Estimates

For companies founded before 2000 (which comprise 99 percent of our data on car owners employed in the Russian private sector) we cannot use the absolute level of the multinational fraction as a proxy for ties to the foreign sector because of the limited time coverage of our data. But if a domestic is hiring relatively more workers from multinationals over the five years for which we have data coverage (meaning that its multinational fraction, starting from zero in 1999, keeps increasing), it could be a sign of strengthening ties to foreign corporations. Once we control for employer-fixed effects, the starting conditions prior to 1999 cancel out, and we can see if increases in this fraction are associated with increased transparency.

There might, however, be unobserved individual characteristics, including but not limited to different preferences for transparency that could lead certain types of workers to join or leave companies hiring workers from foreign corporations. To control for this possible effect in the most general form, we conduct our estimates including employer $\times$ individual fixed effects in all regressions below. We also limit observations to employees of domestic firms who had no prior working experience in foreign-owned firms in our data and who stayed with the same firm from the previous year (we call them "stayers").

Table 5 presents the results of estimating the following equation:

$$\ln E_{i,t}^{R} - \frac{1}{\lambda}\ln C_{i,t} = f_{j(i),i} + \alpha FF_{j(i),t} + \mathbf{b}'\mathbf{S}_{j(i),t} + \mathbf{g}'\mathbf{X}_{i,t} + \phi(t) + \varepsilon_{i,t} \qquad (6)$$

Compared to equation (5) we include employer $\times$ individual fixed effects $f_{j(i)i}$ to control for unobserved individual- and employer-level heterogeneity.[16] As before, $FF_{j(i),t}$ is the (log of) multinational fraction but the interpretation of the coefficient on the variable $FF_{j(i),t}$ is different. In the case of equation (6) it captures how the transparency of income reporting changes for an average "stayer" in a domestic private company when his company hires more workers from multinationals. Table 5 contains separate estimates for the subsamples of employees of private and state-owned domestic establishments (the latter category includes also government agencies). We present the estimates for the absolute level of the multinational fraction as well as its log and also estimate the same equation taking first differences.

Estimation results in the first three columns of Table 5 indicate that an increase in the multinational fraction among employees in domestic private firms is associated with more transparent wages for stayers in all specifications. The economic effects are sizeable. For instance, a one standard deviation increase in (the log of) the fraction of foreign workers is associated with an increase in transparency by about 20 percent.[17] Note also that the effect of an increase in the multinational fraction is limited to Russian firms in the private sector. We do not find any evidence of effects of more hiring from multinationals for transparency in government employment (point estimates suggest even negative effects but are not significant).

[16] Many workers in the "stayers" category remained employed in their respective employers throughout the time of the analysis. For them individual fixed effects absorb employer fixed effects.

[17] See Table A.4 in the appendix for the magnitudes of standard deviations of variables in Table 5.

The absence of any measurable impact of more workers coming from multinationals on transparency in government employment is not surprising. Note that wage contracts in the government sector are largely determined in a centralized way, hence, the management of individual state-owned entities has much less discretion over what wages and how are being paid to its employees than does management in the private sector. Indeed, as we argue in more detail in BML, most "black wages" in government employment captured in our estimation procedure are probably not at all disbursed in the form of cash or other direct payments from the employer but rather represent idiosyncratic extra income from moonlighting, bribes and theft (which are implicitly included in the overall low level of wages in government employment). Hiring from multinationals should have much less effect (if any at all) on unreported earnings from such idiosyncratic sources as opposed to employer-level systematic "black wage" payments in the private sector. These observations are also useful when considering the possible mechanism of the spillovers we observe in the private sector. We will return to this issue below but we first consider some other possible caveats of our analysis.

It is conceivable that our estimations of a positive effect of hiring more from multinationals on transparency may be simply picking up some unobservable time-varying heterogeneity, such as the desire of management to increase transparency, which also leads the firm to hire more from foreign-owned firms. Even if this were the case, our findings are still interpreted in largely the same way because the presence of multinationals is seen to be a catalyst for improved transparency of domestic firms. But it would still be an important distinction from the point of view of how exactly the presence of multinationals tends to affect the culture of domestic firms. Obviously, we cannot include employer-time fixed effects in regression (6) because the fraction of hires from multinationals is constant for a given employer in a given year. But we did re-estimate regression (6) including also the interaction terms between 17 sectors of economic activity and time fixed effects. This allows us to eliminate at least the unobserved heterogeneity coming from sector-specific shocks causing both hiring more from multinationals and increased transparency to happen concurrently. The results (not shown) were qualitatively the same as shown in Table 5.

We also estimated the effects of increased hiring from multinationals separately on reported earnings and car values (contemporaneous and in the subsequent year, to account for slow adjustment in the stock of cars). The results (not shown) indicate that a higher multinational fraction is associated with higher reported earnings but not with higher car values (either current or future) for stayers in the domestic private companies. This renders further support to the interpretation that spillovers from multinationals work primarily through income reporting transparency. Once again, we found no evidence of similar effects (on either reported earnings or car values) in government employment.

4.3. How Does Transparency Spill Over? Some Evidence of Peer Effects

We have seen that exposure to the corporate culture of multinationals at the time the firm was founded, as well as subsequent increase in such exposure through the inflow of employees with experience in foreign-owned companies are associated with increased transparency of car owners who themselves had never worked in a foreign company, at least within the timeframe covered by our data. Moreover, we found this effect in private domestic firms but not in government employment, and we also saw it manifested in increased reported earnings, while car values remained unaffected. Guided by these findings, in this section we try to identify possible mechanisms through which hiring of workers from multinationals increases the transparency of "stayers."

In principle, we can think of at least two possible stories. In one such story an employee is recruited from a foreign corporation to initiate changes in the way the domestic firm operates. We would expect that in such cases a new hire from a foreign company positioned relatively high in the hierarchy would have a larger effect. In other words, the culture of transparency would spill over "vertically," from top to bottom.

A second story is where spillovers occur as a by-product of hiring from multinationals through peer effects. In this story, a domestic employer hires from a multinational for some reasons unrelated to transparency (such as where the worker in a multinational has a particularly desirable set of skills). The increase in transparency is an unintended consequence of this hiring, so that the culture of transparency is transmitted "horizontally." In another closely related version of this story, the domestic company discovers that it has to pay the new hire a relatively more transparent wage than it usually pays to its employees. Then it has to recalibrate the wages of its existing workers employed in similar positions to avoid big ostensible discrepancies in (reported) compensation levels at similar jobs. Newly hired employees from foreign-owned firms thus create a new "benchmark" for how earnings have to be reported in similar positions. In either case, the effects on transparency of stayers will be especially pronounced among employees who are the closest peers of the mover from a foreign-owned firm.

The evidence presented in the previous two sections has already provided us with some insights with regard to the above two stories. For instance, the fact that firms founded in partnership with foreign capital have remained relatively more transparent many years after the foreign capital left (and regardless of how many workers with experience in multinationals they currently employ) may be an indicator of the importance of peer effects, that is, exposure to a more transparent corporate culture as part of one's work experience (in this case the experience of founders and early employees).[18] Also, the absence of measurable effects of increased hiring from multinationals on our measure of transparency of reported earnings in government entities and state-owned enterprises might indicate that unreported incomes not disbursed explicitly by the employer are not influenced by ties to multinationals, suggesting a role for the "benchmarking" story in explaining our findings. This also casts some doubt on the "vertical" spillover story, at least inasmuch as government entities may also try to use recruiting from multinationals to crack down on the culture of moonlighting and theft among their employees.

We now probe more directly for the evidence of both "vertical" and "horizontal" spillovers in our data by constructing several measures designed to capture these and then including them in our regression analyses. To capture "vertical" spillovers we construct two measures. First, for each company in each year we compute the maximum percentile in the wage distribution occupied by a person with prior working experience in a foreign-owned company. Second, for each "stayer" in a domestic company we create a dummy

[18] This is not the only possible explanation, of course. Founders and workers in firms founded jointly with foreign capital during early years of transition are likely to be a select group of individuals and may, in particular, have intrinsic preference for transparency (or aversion to the general rule of the game in the domestic economy), which led them to choose (and to be in turn chosen by) foreign partners when starting their businesses. The demonstration effect of foreign capital would, however, still be important even if this were true as nobody knew how to do business under the rules of the market economy in the USSR.

indicating whether there is a person with prior experience in a foreign-owned firm above him/her in terms of the employer earnings distribution.

To empirically capture "horizontal" spillovers (whether peer effects or "benchmarking"), for each "stayer" in a domestic company we calculate his or her distance from the closest person who came from a foreign-owned firm. We utilized three measures of such distance. First, we compute the minimum distance in the current employer wage percentiles between wages received by a given "stayer" and movers from foreign-owned companies. It is possible, however, that earnings of employees who have just moved from foreign-owned companies might not reflect their true position in the firms' hierarchy due to differences in income reporting. To address this possible problem, we also compute the minimum distance as above, using previous (foreign-owned) employer percentiles for movers.[19]

The third measure we use is based on percentiles in terms of car values. Inasmuch as car values are a better proxy for true earnings than reported earnings, this is likely to be the most adequate measure. Since by construction this measure requires at least one mover from a foreign multinational who is also a car-owner, we can compute it only for a smaller sample of domestic firms. Still, given the widespread presence and heterogeneity of "black wages," this distance is our preferred measure of how similar actually the mover from a multinational is to his or her new colleagues in the recipient Russian firm.

We test how our measure of transparency of earnings (elasticity-adjusted income car gap) for "stayers" in domestic companies is related to the five above distance measures by estimating the following regression:

$$\ln E_{it}^{R} - \frac{1}{\lambda}\ln C_{it} = f_{i,j(i)} + \beta FF_{j(i),t} + \gamma PD_{i,j(i),t} + gX_{it} + \phi(t) + \varepsilon_{i,j(i),t} \qquad (7)$$

Here *PD* represents one or more measures of the intensity of vertical/horizontal spillover as described above as described above. As before, we include employer$\times$individual fixed effects to account for individual and firm level unobserved heterogeneity and we also include the (log of) fraction of workers with prior experience at foreign companies

[19] Just like we did when computing the multinational fraction, we compute all of the above-mentioned measures utilizing the available data on all workers, not just car owners.

because of concerns that changes in our distance measures may simply reflect changes in the overall fraction of employees with prior experience in foreign-owned companies.[20]

Table 6 presents the results of estimating regression (7) for employees of private domestic companies[21]. Measures of vertical spillover have the expected (positive) sign but are not statistically significant and the implied effects are small. Measures of horizontal spillovers, on the other hand, also have the expected (negative) sign and are significantly larger in magnitude even though the standard errors are high. Moreover, the coefficient on our preferred measure, the percentile distance in market values of cars, is both large in magnitude and statistically significant at the 5 percent level despite the smaller sample size. The magnitude of the corresponding coefficient implies that a decrease in car value distance by 10 percentage points for a given "stayer" as a new employee is hired from a foreign-owned firm is associated with an increase in transparency of income reporting also by about 10 percent. It thus seems that "stayers" in domestic companies do tend to experience a significantly larger gain in transparency if they are located closer to a mover from a foreign-owned company in the job quality space, suggesting that peer effects or benchmarking by employers (or both) play a role in transparency of income reporting spilling over to domestic private firms through increased hiring from multinationals.

V. Extensions and Robustness

5.1. Varying Income Elasticity of the Demand for Cars

In the main empirical specifications above we assumed that income elasticity of the demand for the stock of cars is constant throughout the relevant income range. We now relax this assumption. We assume that foreign-owned companies report earnings of their employees truthfully and use this subsample to estimate the demand for the stock of cars with varying income elasticity using the following demand equation:

$$\log C_{i,t} = \alpha(k) + \lambda(k)\log I_{i,t} + \gamma X_{i.t} + \phi(t) + \varepsilon_{i,t} \quad (8)$$

[20] As a company hires more employees from multinationals, the chances to find a mover from a foreign company above in the hierarchy or nearby increase by construction for each individual "stayer." The results, however, are almost exactly the same if the multinational fraction is not included.

[21] We also estimated this regression on the sample of government entities and state-owned enterprises but, once again, found no effects.

Here k is an indicator for a particular income category. To make this demand function continuous we impose the following linear restrictions:

$$\alpha(k) + \lambda(k)\log I(k) = \alpha(k+1) + \lambda(k+1)\log I(k), \text{ for all } k. \quad (9)$$

where $I(k)$ is a cutoff dividing k^{th} and $k+1^{\text{th}}$ income categories.

Table 7 presents the results of estimating equation (8) with restrictions (9) where earnings are divided into three groups: \$1,000-\$5,999; \$6,000-\$16,999; and \$17,000-\$99,999. The cutoffs were chosen so that there is an approximately the same number of observations in each group.[22] The estimated coefficients in Table 7 indicate that income elasticity might indeed be different across different income groups. Note, however, that the estimated elasticity is increasing with income level (it varies from about 0.2 in the poorest group to 0.34-0.43 in the richest group of car owners). In contrast, our measure of hiding, which assumes constant elasticity, might overstate true hiding only if the poorest car owners have stronger demand for cars (at the expense of everything else in their budget) than rich car owners. That would imply a relatively high elasticity of demand for the stock of cars in the lower tail of income distribution, not consistent with estimates presented in Table 7. Hence, there is no evidence that our estimates of hidden earnings based on the constant elasticity are biased upward.

Nonetheless, we did check the robustness of our previous findings by replacing our measure of income-car gap with the constant value of the parameter λ by varying income elasticity parameter estimated in regression (8). Since earnings are misreported in our main sample, we used our estimates of car demand equation to match observations to different income elasticities using observed car values via the following procedure.

For each income bin k and vector of individual specific characteristics X we computed an implied cutoff in car values[23]:

$$\log C(k, X) = \alpha(k) + \lambda(k)\log I(k) + \gamma X + \phi(t). \quad (10)$$

We then assigned a particular value of income elasticity of demand $\lambda(k)$ for a given individual with observed characteristics X by comparing his/her car value C to these cutoffs. Finally, using such assignment we computed a new transparency measure,

[22] We also tried several other specification with different cutoffs and more than 3 income groups. The results were similar and are available upon request.
[23] Since we imposed continuity restrictions (9) it does not matter whether we use k or k+1 bin coefficients.

the income-car gap with varying income elasticity of demand: $\log I_{i,t} - \frac{1}{\lambda(k_{i,t})}\log C_{i,t}$, where $k_{i,t}$ indicates a group to which individual *i* is assigned in period *t* according to his or her car value. Finally, we re-estimated our main empirical specification which links hiring of people from foreign owned companies to changes in transparency of existing employees, using this new transparency measure:

$$\log I_{i,t} - \frac{1}{\lambda(k_{i,t})}\log C_{i,t} = f_{i,j(i)} + \alpha FF_{j(i),t} + bS_{j(i),t} + gX_{i,t} + \phi(t) + G(k_{i,t}) + \varepsilon_{i,t} \quad (12)$$

Compared to our main specification in equation (6) we add dummies ($G(k_{i,t})$) indicating whether individual *i* in year *t* is matched to one of three different elasticities estimated above[24]. Just as in (6) we include individual$\times$employer fixed effects $f_{i,j}$, while $FF_{j,t}$ denotes the fraction of workers with prior experience at foreign multinationals employed at firm *j* in year *t*. Table 8 contains the results of estimating equation (12).

Comparing Table 8 with Table 5 we can see that the patterns are similar. In particular, an increase in the fraction of workers with prior experience in multinationals is still associated with a significant increase in the new transparency measure that accounts for varying income elasticities of the demand for cars. The economic magnitude of the effects implied by estimated coefficients also remains about the same. As before, those patterns are not observed in the state-owned establishments. We also checked the robustness of the results related to our measures of vertical and horizontal spillovers in Table 6 using the value of the parameter λ varying with income and confirmed that they were similar.

5.2. Different Countries of Origin

In the main results section 4.2 above we treated all legitimate foreign-owned companies as homogeneous in their culture. However, there might be differences in corporate ethics even among those companies depending on their country of origin.

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[24] Alternatively one can construct dependent variable subtracting income category coefficients α: $\log I_{i,t} - \left(\log C_{i,t} - \alpha(k_{i,t})\right) / \lambda(k_{i,t})$ and omit the *G* dummies from the regression. We performed such estimation and estimated effects were even larger in magnitude.

To account for these differences, we follow the approach in Guiso, Sapienza, and Zingales (2004, 2006, 2008) and utilize country-specific trust measures from World Values Survey (2009). To each individual moving from a foreign-owned firm to a domestic one we assign the trust measure of the country of origin of his or her previous foreign employer.[25] For employees who never worked in a foreign company we assign the trust measure value of Russia: 0.237. Then for each domestic establishment *j* in any given year *t* we compute trust measure $TR_{j,t}$ as the average trust measure value of its employees in a given year. We then use this trust measure instead of fraction of foreign workers in our main empirical specification (5):

$$\log I_{i,t} - \frac{1}{\lambda}\log C_{i,t} = f_{i,j(i)} + \alpha_P TR_{j(i),t} + \alpha_S FS_{j(i),t} + gX_{i,t} + \phi(t) + \varepsilon_{i,t} \qquad (14)$$

Specification (1) in Table 9 contains the results of estimating equation (14). The estimated coefficient has the predicted sign but is imprecisely measured and not statistically significant at conventional levels. This is perhaps not surprising given that most companies identified as foreign in our sample come from relatively few advanced Western countries (35 percent of all foreign-owned companies in our data come from the United States, about 20 percent from Germany, about 8 percent from the UK and so on).

We thus decided to use a somewhat different approach. Foreign companies, even those originating in the same country, employ different fractions of workers from their home countries as opposed to local Russian employees (or workers from other countries). We conjecture that for any given foreign-owned company, the higher the fraction of employees who are citizens of "high-trust" countries, the larger will be the impact of its corporate culture on its Russian employees. We then constructed an alternative measure of trust for a given foreign company by averaging the trust measure value for all of its Moscow branch employees on the basis of their citizenship. The breakdown of employment by citizenship data is available only for 2003, so we assign the measure calculated as above to all previous years for the same company. Also, since the influence of people at the top of the firm hierarchy might be correspondingly larger, we calculated

[25] The country's of origin trust measure is defined as the average fraction of respondents who answered affirmatively to the question "*Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?"* Note that this measure is assigned to all movers from foreign-owned firm, regardless of their own nationality. In fact, our linking process of observations on individuals over time leaves only Russian nationals in the main sample.

the same measure counting only employees in the top 1, 5, and 10 percent of earnings distribution in a given foreign-owned company. As before, we then assign these company-specific trust measures to all individuals (Russian citizens) who move from the given foreign company to a Russian employer.

For each domestic firm in a given year we then compute the mean trust of all of its employees imputing for all stayers and movers from Russian companies the trust value for Russia (0.237) and for movers from foreign companies, the trust measure of the previous foreign employer as computed above. In this approach, the mean trust measures for domestic companies would vary differently depending on mean trust levels in foreign-owned firms they hired their new employees from, even though the country of origin of the multinationals might be the same. We then estimate the same equation (14) above using this newly computed trust measures.

In specifications (2)-(5) of Table 9 we show four results reflecting different trust measures assigned to movers from foreign-owned companies; the one based on all employees' citizenship, and the other three based on the top 10, 5 and 1 percent. Hiring employees from foreign-owned companies whose trust measure based on all employees' citizenship and on the citizenship of the top 10 percent of its earners is higher has a large and statistically significant (at 10 percent) positive effect on the transparency of stayers in domestic private companies. The estimated coefficients indicate that an increase of a one standard deviation in the trust measure of new hires is associated with about 6-15 percent increase in transparency for stayers in domestic companies. Coefficients for trust measures computed using top 1 and 5 of employees are less precisely measured but the implied effects are similar (7 and 10 percent, respectively, for a one standard deviation increase in the trust measure). It is worth noting that coefficients of variation for all trust measures in our data are quite small,[26] but even for those small changes in trust measures we find sizeable effects on transparency.

5.3. Reverse Spillovers

So far we have examined the evidence of the flow of corporate standards from foreign-owned to domestic private sector. It is legitimate, however, to ask if spillovers

[26] See Table A.4 in the appendix for summary statistics for those variables.

might also go into the opposite direction. In other words, does movement of employees from Russian firms result in lowering the transparency standards of multinationals operating in Russia? For example, if one reason why multinationals behave more transparently compared to domestic firms is because they just lack the necessary connections to avoid scrutiny, hiring local employees with good connections may "help" to resolve this issue and allow foreign-owned firms to also start hiding more. While a full investigation of this possible phenomenon is beyond the scope of the present analysis, we briefly probe here for the evidence that might be suggestive of such "reverse spillovers."

In each year for each foreign-owned company we compute the fraction of its employees who have joined it from domestic private (*FP*) or state-owned company (*FS*). Since our sample window is between 1999 and 2003 those fractions are once again zero by construction up to the year 2000. But just as we did in Section 4.2.3, we can look at how changes in those fractions affect the transparency of foreign-owned companies while including individual $\times$ employer fixed effects, which will cancel out the effects of unobserved initial values of those fractions. Thus, we estimate an equation similar to (6) but for income-car gap in foreign-owned companies:

$$\log I_{i,t} - \frac{1}{\lambda}\log C_{i,t} = f_{i,j(i)} + \alpha_P FP_{j(i),t} + \alpha_S FS_{j(i),t} + gX_{i,t} + \phi(t) + \varepsilon_{i,t} \qquad (15)$$

Here $FP_{j(i),t}$, $FS_{j(i),t}$ are (log of) fractions of workers who moved from domestic firms and from state-owned establishments to a given foreign employer. Among individual controls *X* we include the individual position within the firm[27]. As before, we estimate this regression only for the sample of employees of foreign companies who themselves did not move from domestic establishments.

In specifications (1)-(4) Table 10 we present estimation results of equation (15) for both the level and the log of fraction of workers who previously worked in private and domestic companies. The effects are statistically significant only for the level of fraction of workers from private companies[28]. Estimated coefficient implies a decrease in transparency by 10 percent for a one standard deviation increase in fraction of workers

[27] We do not include the observed firm size because it is a size of the Russian subsidiary of a foreign company and as such might be different from the actual size of the multinational. The results are similar if we include it. We would like to thank Luigi Guiso for raising this point.

[28] The combined fraction of workers from domestic establishments (including both private and state-owned) is significant at only the 10 percent level.

from domestic private companies. The effect is small and not significant for the logs of those fractions.[29]

In specifications (5)-(8) we re-estimated equation (15) now limiting the sample to foreign companies with more than 50 employees (not necessarily car-owners) in their Moscow branch. Estimated coefficients for fraction of domestic workers decrease by a factor of three and are no longer significant. Overall, it seems that while there might be some reverse spillovers in transparency from domestic to foreign-owned companies, especially for smaller establishments, the empirical evidence in their favor is less compelling than for spillovers from foreign to domestic companies documented in the main text above.

5.4. Robustness

One possible concern about our estimation results centers around the argument that some employees, especially at the top of the firm hierarchy may have less need for personal cars because they may have access to company cars provided to them as part of their compensation. To address this possible concern, we re-estimated all our regressions while dropped from the sample workers whose compensation was among the top 5 percentile of earners in their respective employers (which should include all top management that could have access to company cars). Table 11 presents the estimation results of our main regression equation (6) for this subsample. As can be seen, the magnitudes of the effects are even larger than for the whole sample. The results in all other regressions presented in the main text are also completely robust to excluding top management from our sample.

Among other checks, we have examined whether our results are robust to excluding female car owners and also to excluding workers below a certain percentile (such as the median) in the wage distribution of their respective employers (to restrict our attention to only those above a certain threshold of productivity within their firms). The results were very similar. We also experimented with various car value cutoffs and we

[29] To be included in specification (4), a given foreign-owned company had to have a positive fraction of movers from both domestic private and state-owned entities, which is why the number of observations is smaller than in column (2). The same applies to the difference in the number of observations between columns (6) and (8) in the same table.

estimated the model without imposing any restrictions on car values or incomes. And we probed whether our results might be affected by firm-level selection by limiting the sample to only those employers that were present in all five databases. In all these cases the results were very similar to those presented in the main text. Details are available upon request.

VI. Conclusions

We have examined the difference in corporate culture between multinationals and domestic private firms in the transitional economy of Russia. Using administrative records on official wages and salaries matched to car ownership data we found that in 1999-2003 foreign-owned firms reported on average four times higher earnings of their employees than did domestic private firms for the same car values and other characteristics. There is strong support in the data for the widespread perception that Russian firms hide a lion's share of actual employee compensation. One implication of this finding is that estimates that show foreign-owned firms to have much higher labor productivity than their domestic counterparts may be overstating the actual efficiency gap by not taking proper account of hidden earnings (and also hidden sales and profits) in domestic firms.

Another implication, on which we have focused in this paper, is that there is a potential for foreign firms to affect positively the transparency standards of domestic firms. We argued that this could be an important channel through which foreign direct investment may contribute to improved efficiency of the recipient economy because the system of unofficial worker compensation, though privately profitable, is likely to be inefficient overall[30].

We found that private Russian firms founded in partnership with foreign capital were twice as transparent in reporting earnings of their employees as other private Russian companies, even though most of them were currently entirely owned by Russian capital. We also documented positive relation between transparency and increased hiring from multinationals: an increase in the fraction of workers hired from foreign

[30] Among other things, it involves high transaction costs, unnecessary barriers on labor (and general resource) reallocation due to inherent trust problems, and deprive governments of tax revenues and workers of the employer contributions to the retirement fund.

corporations by one standard deviation was associated with a 20 percent increase in the transparency of reported incomes for workers who themselves did not come from multinationals, controlling for employer$\times$individual fixed-effects.

Of course, we cannot completely rule out the possibility that there were some other time-varying effects that caused both the fraction of hires from multinationals and the degree of transparency to increase concurrently in affected firms. But we found that including sector of economic activity$\times$year dummies to control for time-varying sector specific (unobservable) shocks did not change the results. We also looked for evidence that transparency of Russian firms may be increasing disproportionately if they hired top executives from multinationals (which could be interpreted as evidence of a deliberate efforts to increase transparency by hiring from multinationals) but we did not find much support for this channel in our data.

Instead, we found patterns that point to the importance of peer effects and/or "benchmarking" of wages where domestic private firms adjust officially paid wages and salaries to incumbent workers positioned similarly to new hires from multinationals in terms of their job responsibilities. While the evidence is somewhat tentative, there is support for the notion that domestic firms that find it important to hire workers from multinationals for reasons not necessarily related to transparency (such as perhaps their skills), may as a by-product be "pushed" into becoming more transparent.

Culture in general and corporate culture in particular is stubborn and hard to change. There is no better evidence of this than the struggles of the Russian economy and other economies of the former Soviet Union over the 20 years that have elapsed since those countries bid farewell to their "socialist" system. But we also know that eventually cultural changes do come about in response to economic incentives. Foreign capital and especially foreign direct investment may thus play an important role in diffusing not just better technologies and management practices but also the culture of transparent, arms-length transactions in recipient countries suffering from inefficient, non-transparent, and insider-oriented culture of doing business. Our paper has shown that there is indeed some evidence of such diffusion, offering a glimmer of hope for the Russian economy.

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Tables

Table 1. Summary statistics:

Means of	Private, not foreign owned	Government and SOE	Foreign-owned
Car Values (C)	7,285	6,288	7,734
	(11,987)	(9,605)	(10,083)
Incomes (I)	3,749	3,059	15,807
	(6,939)	(4,538)	(15,896)
Means ratio (C)/(I)	1.94	2.06	0.49
Age	39.7	41.5	35.2
	(9.8)	(10.0)	(8.9)
Fraction Male	0.78	0.71	0.66
	(0.42)	(0.45)	(0.47)
Percentile in employer earning distribution	0.71	0.66	0.67
	(0.24)	(0.26)	(0.25)
Employer size (number of employees)	1,752	8,811	684
	(4,282)	(14,886)	(1,269)
Fraction of car owners in the data	0.144	0.096	0.205
	(0.106)	(0.062)	(0.120)
Number of observations	187,326	188,679	15,047

Within the private sector:	Not foreign-related	Foreign-related	Foreign-related, top 10 percent
Car Values (C)	7,260	7,319	8,954
	(12,108)	(11,742)	(13,220)
Incomes (I)	2,967	5,228	6,112
	(5,757)	(8,552)	(11,623)
Means ratio (C)/(I)	2.45	1.40	1.46
Age	40.1	38.9	36.0
	(9.7)	(10.0)	(9.4)
Fraction Male	0.79	0.76	0.72
	(0.41)	(0.43)	(0.45)
Percentile in employer earning distribution	0.70	0.71	0.69
	(0.25)	(0.24)	(0.25)
Employer size (number of employees)	790	3,577	383
	(2,108)	(6,292)	(619)
Fraction of car owners in the data	0.157	0.120	0.182
	(0.115)	(0.080)	(0.113)
Number of observations	122,557	64,664	6,543

Source: Authors' estimates using Moscow income and car registry databases for 1999-2003. Excluding car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. All values in 1999 US dollars using market exchange rates between the US dollar and the ruble and adjusted for inflation using the US Consumer Price Index. Foreign-related firms are those with the non-zero observed fraction of workers with experience in foreign-owned firm. "Top 10 percent" refers to the top 10 percent of foreign-related firms with the highest fraction of workers with experience in foreign-owned firms. Numbers in brackets are standard deviations.

Table 2. Ownership, sectors of economic activity and transparency

	Pooled OLS	Median regression	Individual fixed-effects
	Ownership: Private domestic is the omitted category		
Foreign ownership	1.656***	1.547***	1.132***
	(0.030)	(0.023)	(0.055)
State ownership	0.252***	0.233***	0.261***
	(0.017)	(0.013)	(0.028)
Log number employees	0.184***	0.173***	0.015***
	(0.004)	(0.003)	(0.005)
	Select sectors of economic activity (omitted sector, IT and)		
Banking and finance	-0.581***	-0.520***	-0.480***
	(0.035)	(0.025)	(0.055)
Utilities	0.030	0.096***	0.608***
	(0.038)	(0.031)	(0.089)
Wholesale and retail trade	-0.636***	-0.591***	-0.323***
	(0.033)	(0.024)	(0.050)
Manufacturing	0.034	0.102***	0.270***
	(0.030)	(0.024)	(0.049)
Services	-0.378***	-0.287***	-0.115**
	(0.034)	(0.025)	(0.051)
Age	0.020***	0.022***	
	(0.001)	(0.000)	
Male dummy	0.090***	0.034***	
	(0.014)	(0.010)	
Percentile in employer earnings distribution	2.379***	2.321***	2.595***
	(0.021)	(0.017)	(0.019)
	Year dummies: omitted year 1999		
2000	0.127***	0.140***	0.371***
	(0.009)	(0.014)	(0.008)
2001	0.479***	0.483***	0.898***
	(0.011)	(0.014)	(0.008)
2002	0.620***	0.690***	1.222***
	(0.012)	(0.014)	(0.009)
2003	0.480***	0.608***	1.301***
	(0.012)	(0.014)	(0.009)
Constant	-20.538***	-20.272***	-19.341***
	(0.042)	(0.034)	(0.052)
# of obs. (individuals)	397,071 (208,134)	397,071 (208,134)	397,277 (208,251)
Adjusted (pseudo-) R-squared	0.079	0.074	0.796

Notes: The dependent variable is the "income-car gap", defined as the difference between Log of inflation-adjusted reported earnings and inflation and income elasticity-adjusted Log of car values: $\log E^R - 1/\lambda \log C$. Pooled OLS with robust standard errors clustered by employers in parentheses. ***, **, and * indicate significance at 1 percent, 5 percent and 10 percent levels, respectively. Excluding car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60.

Table 3. Transparency and founding background

	(1)	(2)	(3)	(4)
	OLS		Median Regression	
Foreign partner at founding dummy	0.524***	0.503**	0.491***	0.424***
	(0.174)	(0.214)	(0.050)	(0.063)
Log number of employees	0.157***	0.144***	0.145***	0.160***
	(0.036)	(0.047)	(0.008)	(0.014)
Constant	-19.470***	-18.854***	-19.317***	-19.005***
	(0.429)	(0.612)	(0.180)	(0.305)
Other controls	Yes	Yes	Yes	Yes
Founding year dummies	No	Yes	No	Yes
# of observations (employers)	77,312 (1,254)	35,499 (712)	77,312 (1,254)	35,499 (712)
Adjusted (pseudo-) R-squared	0.123	0.109	0.069	0.065

Notes: The dependent variable is the income-car gap as defined in Table 2. Pooled OLS with robust standard errors clustered by employers in parentheses. ***, **, and * indicate significance at 1 percent, 5 percent and 10 percent levels, respectively. Excluding car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. Other controls in all specifications include 17 dummies for sectors of economic activity, time fixed effects, age, age squared, gender, and percentile in the employer's earning distribution. Specifications (2) and (4) include 16 dummies for years the company was founded (between 1988 and 2003).

Table 4. Transparency and fraction of workers with prior experience in multinationals in firms founded after 1999

	(1) (Pooled OLS)	(2) (Median regression)	(3) (Pooled OLS)
	LogIncCar = Log Income – 1/λ Log Car Value		
Dummy for a non-zero fraction of workers with prior multinational experience	0.680*	0.481*	
	(0.379)	(0.257)	
Log fraction of workers with prior multinational experience			0.814***
			(0.284)
Log number of employees	0.386***	0.411***	0.743***
	(0.142)	(0.092)	(0.203)
Constant	-15.878***	-15.894***	-13.497***
	(1.850)	(1.579)	(1.520)
Other controls	Yes	Yes	Yes
Founding year controls	Yes	Yes	Yes
# of observations (employers)	1,813 (96)	1,813 (96)	1,459 (68)
Adjusted (pseudo-) R-squared	0.117	0.069	0.123

Notes: The dependent variable is the income-car gap as defined in Table 2. Pooled OLS with robust standard errors clustered by employers in parentheses. ***, **, and * indicate significance at 1 percent, 5 percent and 10 percent levels, respectively. Excluding car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. Other controls in all specifications include 17 dummies for sectors of economic activity, time fixed effects, age, age squared, gender, and percentile in the employer's earning distribution. Specifications (1) and (2) include only private domestic companies founded in 1999-2003. Specification II includes 4 dummies for years the company was founded (between 2000 and 2003). Specification (3) limits the sample to firms that had non-zero fraction of workers with prior multinational experience.

Table 5. Fraction of workers with prior experience in multinationals and the transparency of "stayers": Fixed-effects estimates

Variables	(1) LogIncCar = Log Income – 1/λ Log Car Value	(2)	(3) DLogIncCar	(4) LogIncCar = Log Income – 1/λ Log Car Value	(5)	(6) DLogIncCar
Ownership	Private	Private	Private	Government	Government	Government
Log fraction of workers with prior experience in FOF	0.166*** (0.059)			-0.035 (0.028)		
Fraction of workers with prior experience in FOF		12.340* (6.445)			-42.266* (24.415)	
First difference in log fraction with prior experience in FOF			0.117*** (0.033)			-0.023 (0.021)
Log number of employees	-0.219 (0.136)	-0.244* (0.137)		0.019 (0.056)	0.050 (0.056)	
First difference in log number of employees			0.312*** (0.073)			0.097*** (0.037)
Percentile in employer earnings distribution	2.417*** (0.245)	2.415*** (0.245)	0.437*** (0.092)	2.536*** (0.123)	2.542*** (0.123)	0.174*** (0.053)
Male dummy			0.208*** (0.041)			0.266*** (0.024)
Constant	-15.036*** (1.034)	-15.963*** (0.981)	-0.109 (0.100)	-18.109*** (0.526)	-18.082*** (0.500)	0.000 (0.059)
Employer × individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,609	28,609	12,439	52,667	52,667	26,605
R-squared	0.947	0.947	0.023	0.944	0.944	0.013

Notes: The dependent variables are the income-car gap as defined in Table 2 and the first difference in income-car gap as described in the main text. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% respectively. Excluding car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. Sample is limited to workers with no prior experience in foreign-owned firms employed by a given employer for two consecutive years. Specifications (1)-(3) are estimated for the sample of employees of domestic private companies, specifications (4)-(6) for employees of government entities and state-owned enterprises. All specifications include employer × individual and time fixed effects.

Table 6. Vertical vs Horizontal Spillovers (Estimations of regression (7))

	(1)	(2)	(3)	(4)	(5)	(6)
	LogIncCar = Log Income – 1/λ Log Car Value					
Log fraction of workers with prior experience in FOF	0.157***	0.123**	0.296	0.160***	0.160***	0.140
	(0.059)	(0.063)	(0.209)	(0.059)	(0.059)	(0.229)
Percentile distance	-0.038					0.238
	(0.131)					(0.621)
Percentile distance (last)		-0.077				-0.128
		(0.135)				(0.413)
Percentile distance (car values)			-1.009**			-1.019*
			(0.497)			(0.524)
Maximum percentile with a foreign mover				0.049		0.367
				(0.109)		(0.683)
Dummy for a mover from a foreign employer above					0.041	0.039
					(0.067)	(0.250)
Log number of employees	-0.220	-0.187	-0.162	-0.223	-0.221	-0.275
	(0.136)	(0.142)	(0.397)	(0.136)	(0.136)	(0.402)
Percentile in EED	2.442***	2.536***	2.529***	2.412***	2.452***	2.576***
	(0.248)	(0.258)	(0.734)	(0.245)	(0.252)	(0.746)
Constant	-15.076***	-15.588***	-14.908***	-15.059***	-15.090***	-15.181***
	(1.033)	(1.082)	(3.101)	(1.034)	(1.034)	(3.157)
Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Employer × Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,526	26,831	9,198	28,609	28,609	8,723
R-squared	0.947	0.948	0.963	0.947	0.947	0.962

Notes: The dependent variable is the income-car gap as defined in Table 2. Excluding car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. Sample is limited to those who continued employment at a given private domestic employer. See notes to Table 9 for the explanation of variables. All specifications include employer × individual and time fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

Table 7: Varying Income Elasticity of Demand for Cars

VARIABLES	(1)	(2)	(3)	(4)
	Dependent Variable: Log of Car Value			
log Income × Income Bin1	0.195***	0.162***		
	(0.050)	(0.050)		
log Income × Income Bin2	0.317***	0.260***		
	(0.062)	(0.062)		
log Income × Income Bin3	0.428***	0.337***		
	(0.102)	(0.101)		
log Income			0.282***	0.231***
			(0.023)	(0.024)
Age	-0.034**	-0.022	-0.030*	-0.019
	(0.017)	(0.018)	(0.017)	(0.018)
Age-squared	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Male gender	0.162***	0.104**	0.159***	0.103**
	(0.041)	(0.042)	(0.041)	(0.042)
Income Bin1	2.136**	1.601		
	(1.060)	(1.057)		
Income Bin2	1.077	0.753		
	(1.394)	(1.381)		
Constant	4.678***	5.528***	5.963***	6.512***
	(1.062)	(1.057)	(0.340)	(0.353)
Sector of Economic Activity FE	No	Yes	No	Yes
Observations	5,660	5,660	5,660	5,660
R-squared			0.106	0.124

Notes: Dependent variables is log of total market value of cars for a given individual. Sample is limited to employees of foreign-owned companies with annual incomes above $1,000. Incomes categories are $1000-$6,000; $6,000-$17,000 and $17,000-$100,000. Specifications (2) and (4) include sectors of economic activity dummies. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

Table 8: Fraction foreign and varying income elasticity of demand for cars.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Dependent variable: LogIncCar = Log Income – 1/λ(*k*) Log Car Value							
	Private	Private	Private	Private	Government	Government	Government	Government
log fraction foreign	0.101**	0.076*			-0.043**	-0.050*		
	(0.043)	(0.046)			(0.021)	(0.027)		
fraction foreign			9.141**	8.703***			-39.351**	-45.863**
			(3.549)	(3.377)			(17.490)	(20.056)
log # employees	-0.180*	-0.186	-0.193*	-0.183	0.031	0.028	0.063	0.051
	(0.100)	(0.117)	(0.100)	(0.118)	(0.044)	(0.055)	(0.043)	(0.053)
Percentile	2.690***	2.708***	2.691***	2.708***	2.621***	2.649***	2.626***	2.654***
	(0.190)	(0.189)	(0.190)	(0.189)	(0.101)	(0.101)	(0.101)	(0.101)
Constant	-12.877***	-12.828***	-13.466***	-13.372***	-15.248***	-14.699***	-15.159***	-14.482***
	(0.758)	(0.890)	(0.720)	(0.856)	(0.407)	(0.494)	(0.391)	(0.480)
Sector × Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Individual × EmployerFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,054	26,054	26,054	26,054	48,539	48,539	48,539	48,539
R-squared	0.997	0.998	0.997	0.998	0.998	0.998	0.998	0.998

Notes: The dependent variable is the "income-car gap", defined as the difference between Log of reported earnings and income elasticity-adjusted Log of car values: $\log E^R - 1/\lambda(k)\log C$. Income elasticity of demand $\lambda(k)$ varies by income categories *k*. See details of assignment in the main text. Sample excludes car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. Sample is limited to workers with no prior experience in foreign-owned firms employed by a given employer for two consecutive years. Specifications (1)-(4) are estimated for the sample of employees of domestic private companies, specifications (5)-(8) for employees of government entities and state-owned enterprises. All specifications include employer × individual, income category, and time fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

Table 9: Heterogeneity in Corporate Culture of Foreign Multinationals
And Transparency of Domestic Companies.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Dependent variable: LogIncCar = Log Income – 1/λ Log Car Value				
Mean Trust: Company country of registration	0.705 (0.619)				
Mean Trust: Citizenship		31.096* (17.603)			
Mean Trust: Citizenship (top 1% measure)			3.782 (2.301)		
Mean Trust: Citizenship (top 5% measure)				13.415 (9.261)	
Mean Trust: Citizenship (top 10% measure)					25.702* (13.140)
Log # employees	-0.273** (0.131)	-0.297** (0.132)	-0.276** (0.131)	-0.279** (0.131)	-0.283** (0.131)
Percentile in EED	2.460*** (0.234)	2.460*** (0.235)	2.472*** (0.234)	2.468*** (0.234)	2.478*** (0.235)
Constant	-15.729*** (0.943)	-15.529*** (0.947)	-15.695*** (0.938)	-15.673*** (0.937)	-15.646*** (0.936)
Individual × EmployerFE	Yes	Yes	Yes	Yes	Yes
Observations	30,080	30,080	30,080	30,080	30,080
R-squared	0.948	0.948	0.948	0.948	0.948

Notes: The dependent variables is the income-car gap as defined in Table 2 and described in the main text. Sample is limited to workers with no prior experience in foreign-owned firms employed by a given private domestic employer for two consecutive years. Sample excludes car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. Trust values are computing using World Values taking averages across all employees of a given domestic employer. Trust values for movers from foreign companies are assigned on the basis of their past foreign employer's country of registration, citizenship of its (all, top 1, 5, and 10 percent) employees. All specifications include employer × individual and time fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

Table 10: Reverse Spillovers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Dependent variable: LogIncCar = Log Income – 1/λ Log Car Value							
Fraction domestic	-2.594*				-0.867			
	(1.458)				(2.742)			
log fraction domestic		-0.040				-0.026		
		(0.115)				(0.117)		
Fraction private			-3.043**				-0.940	
			(1.415)				(3.370)	
Fraction state-owned			-0.969				-0.751	
			(4.361)				(5.328)	
log fraction private				-0.001				-0.001
				(0.126)				(0.125)
log fraction state-owned				-0.143				-0.143
				(0.122)				(0.122)
Own Percentile	2.842***	3.104***	2.838***	3.286***	3.138***	3.138***	3.138***	3.286***
	(0.322)	(0.355)	(0.322)	(0.422)	(0.357)	(0.372)	(0.357)	(0.421)
Constant	-16.442***	-16.931***	-16.444***	-17.838***	-16.688***	-16.892***	-16.688***	-17.840***
	(0.252)	(0.536)	(0.252)	(0.824)	(0.285)	(0.557)	(0.284)	(0.823)
Individual × EmployerFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,974	6,986	7,974	5,180	7,186	6,714	7,186	5,170
R-squared	0.910	0.913	0.910	0.920	0.910	0.911	0.910	0.920

Notes: The dependent variable is the "income-car gap", defined in Table 2 with constant income elasticity of demand for cars. Sample excludes car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. Specifications (5)-(8) limit the sample to foreign employers with 50 or more employees in any give year. "(Log) Fraction (domestic, private, state-owned)" shows the (log)fraction of employees with previous experience in any domestic, private and state-owned employers currently working at a given foreign company. Own percentile in wage distribution is included but nor reported. Sample is limited to those who continued employment at a given foreign-owned employer. All specifications include employer×individual and time fixed effects. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% respectively.

Table 11. Robustness (correcting for company cars):
Subsample of employees below 95th percentile of wage distribution

Variables	(1) LogIncCar = Log Income – 1/λ Log Car Value	(2)	(3) DLogIncCar	(4) LogIncCar = Log Income – 1/λ Log Car Value	(5)	(6) DLogIncCar
Ownership	Private	Private	Private	Government	Government	Government
Log fraction of workers with prior experience in FOF	0.161**			0.001		
	(0.065)			(0.030)		
Fraction of workers with prior experience in FOF		14.130**			-39.834	
		(6.835)			(26.842)	
First difference in log fraction with prior experience in FOF			0.131***			-0.025
			(0.035)			(0.022)
Log number of employees	-0.337**	-0.372**		-0.048	-0.029	
	(0.166)	(0.168)		(0.068)	(0.067)	
First difference in log number of employees			0.366***			0.097**
			(0.078)			(0.043)
Percentile in employer earnings distribution	2.432***	2.435***	0.620***	2.475***	2.484***	0.281***
	(0.266)	(0.266)	(0.104)	(0.130)	(0.130)	(0.060)
Male dummy			0.191***			0.276***
			(0.044)			(0.025)
Constant	-14.270***	-15.111***	-0.225**	-17.220***	-17.369***	-0.075
	(1.267)	(1.201)	(0.107)	(0.617)	(0.594)	(0.062)
Employer × individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,503	23,503	10,287	45,455	45,455	22,811
R-squared	0.955	0.955	0.024	0.951	0.951	0.014

Notes: The dependent variables are the income-car gap as defined in Table 2 and the first difference in Income-car gap as described in the main text. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% respectively. Excluding car owners with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60. Sample is limited to workers with no prior experience in foreign-owned firms employed by a given employer for two consecutive years below 95th percentiles in employer's earnings distribution. Specifications (1)-(4) are estimated for the sample of employees of domestic private companies, specifications (5)-(8) for employees of government entities and state-owned enterprises. All specifications include employer × individual and time fixed effects.

Appendix 1. Details About the Data and Sample Construction

Data sources

We employed two separate sets of data.

Vehicle Registration Database, 2005: Contains the list of all recorded instances of vehicle registrations in Moscow as of April 2005, along with the corresponding list of owners. The former provides the detailed description of vehicle characteristics including model, make, year of manufacturing, license plate number, unique Vehicle Identifying Number (VIN), and the date of registration. The latter contains data on each owner's full name, date of birth, residential address and passport number. Each entry in the vehicle database represents an instance of registration. Repeated registrations of the same vehicle are recorded as separate entries. We therefore define continuous periods of ownership for each car as intervals between its consecutive registrations by distinct owners. And to find all relevant entries that correspond to a given car we use its VIN number. The total number of raw entries is 8,308,881 vehicle registrations and 8,141,122 owners.

Administrative Databases of Income, 1999–2003: This is a collection of five separate databases filed by all registered employers (sources of income) in Moscow for their employees (recipients of income). Each database covers one year between 1999–2003. Individual records in all of the five files provide full names, dates of birth, personal tax IDs, passport numbers, residential addresses, annual gross and taxable incomes, employers' names and employers' state-issued registration IDs. The total number of raw entries in each database is as follows: 8,711,103 (1999); 10,361,320 (2000); 10,019,144 (2001); 7,029,376 (2002); 9,355,493 (2003).

Data issues

All datasets above appear to have originated from manually digitized paper-based records and that leads to the following common problems:

Errors and missing data: A substantial number of entries contain artifacts of manual input: violations of the format, misspellings, typos, idiosyncratic abbreviations, missing data in certain fields, etc. This poses a challenge for matching entries across databases, as it reduces the amount and reliability of identifying information. As a result, we were not able to positively identify all legitimate matches, however, due to the random nature of imperfections in the data, we do not expect these missing matches to cause any systematic bias in our estimates.

Duplicate entries: We found that approximately 10 percent of all entries in our datasets are in fact virtual duplicates of some other entries contained in the same files. Some of them are fully identical to (and are thus indistinguishable from) the originals; the rest have slight modifications compared to the originals, caused usually by typos or partially missing data. As explained in the main text, we decided to use only those individuals for whom we had only one entry in each of the income databases, thus eliminating all individuals with duplicate entries (as well as those with multiple sources of income in any year).

Detailed sample construction procedure

We first used combinations of full name, date of birth and address to provisionally match individuals in income databases for different years and to their vehicle ownership records. We then used additional identifying information (personal tax ID, passport number, etc.) available in those matched records to find other matches that were not identified before. Finally, in our working sample we kept only the individuals that had at most one entry in any of the five income databases.

In more detail, the selection procedure was as follows:

Step 1: We started by eliminating poor quality data from all databases to increase the efficiency of subsequent matching. Specifically, we left out all entries that either had inconsistencies in full names (abbreviations, obvious typos or non-alphabetic characters), or lacked information on the date of birth, or address.

Step 2: We then used the five income databases to create linking tables that established connections between the same individuals within each database and between each pair of them. This process relied on the iterative matching procedure that leveraged all individual identifying information found in preceding iterations when searching for other possible matches in subsequent iterations.

Step 3: Based on the linking tables obtained in the previous step, we created five cross-sections of "single-entry" individuals, separately for each of the five years from 1999-2003. More precisely, an individual was left in the sample if (1) he or she was present exactly one time in the database for a given year (no other related entries in that year) and (2) he or she had at most one related entry in each of the remaining four databases. This sample, consisting of about 26.9 million observations (about 60 percent of all initial raw entries in all 5 income databases), was used to calculate various employer-specific variables, such as the multinational fraction, used in the estimations in the main text.

Step 4: The auto registry database was used to match owners to all of their vehicles. If an individual owned multiple vehicles, the market values of all such vehicles (assigned as explained in Appendix 2 below) were added together. We then matched car owners with "single-entry" individuals in each of the five income databases obtained in the previous step. This produced 2,913,359 matched observations on individuals who owned at least one car in at least one of the five years from 1999-2003 and were present in at least one of the "single-entry" income databases as explained in the previous step. From this sample of all car owners matched to their income records we constructed the sample used for estimation purposes by eliminating cars with missing VINs for which we could not determine the exact time period during which an individual owned a given car.

Research variables

For each individual in our sample we were able to directly obtain the following information about research variables used in estimation: age (from the information about the date of birth), name and state-issued registration ID of the employer (income source) for 1999-2003; the amount of income earned (received) from the employer (income source); make, model and year of all owned cars (if any); estimated market value of all owned cars (if any) as imputed using the procedure explained in Appendix 2.

In addition, we created the following research variables from the available data:

Gender: Imputed from gender-specific endings of middle names, which are characteristic of the Russian language.

Sector classification and type of ownership: We classified 14,000 distinct primary employers in our sample into 19 sectors and also assigned each of them to one of the three types of ownership (see Appendix 3 for more details). Namely, we checked the presence of sector-specific keywords (such as bank, insurance, factory, police, etc.) in employers' names to do the initial automatic sector assignment and then manually assigned sectors to the employers that were left out by the script. Similarly, we used another list of keywords to infer the type of ownership (e. g. JSC, Ltd, State, etc.) and we used the website http://querycom.ru/ which provided ownership information for companies using their state-issued registration IDs we have in our data. We then manually resolved all the remaining undetermined cases and also manually checked all companies provisionally classified as foreign-owned to determine whether it was owned by a western corporation or was an offshore controlled by Russian capital.

Employer Size: This was obtained by counting the total number of individuals who received payments from a given employer (income source) in a given year.

Percentile in Employer Earnings Distribution (EED): This was obtained as the percentile of an individual's income in the overall earnings distribution of his/her employer in a given year.

Even though all the data used by us came from the public domain, to ensure privacy we have purged all the individual identifying information (names, addresses, id numbers) after we finished the construction of the sample. All the data used in the paper (without individual identifying information) and our estimation codes will be available for the purposes of replicating our results. We can also provide the scripts used to clean the data and to conduct the selection/matching process described in steps 1-4 above, which can be employed to replicate our sample construction procedure using the original databases.

Appendix 2. Imputation of car values

We develop a procedure to assign prices to the vehicles owned by individuals in our sample. For each car, our data contain the car's make, model and the year it was produced. For example: "Make: Hyundai; Model: Avant; Production year: 1999," or "Make: Jaguar; Model: XJ6; Production year: 1993." No information on the presence of optional features or the vehicle's condition is available. Hence, we could only assign prices to vehicles based on the median market value of cars of the same make, model and year of production. The details of the procedure used to impute prices are described below.

Determining used/new status

New cars sell at a substantial premium over used cars, so accurately assigning a price to a vehicle requires determining whether it was purchased new or used. To do so, we used Vehicle Identification Numbers (VINs) to search the Vehicle Registration Database and determine the car's date of first registry. We dropped vehicles lacking a valid VIN, but this affected only a relatively small number of older, low-value vehicles.

We designated a car "new" if it was first registered in the year it was produced and in the name of the current owner. We considered a car "used" if the database showed prior registrations by different owners. We also considered a car "used" if either: (i) it was produced two or more years prior to the date of the first recorded purchase, or (ii) the first recorded purchase occurred after June 30th of the year following the production year. This (somewhat arbitrary) rule applied to less than 5 percent of cars in our sample (these cars also all proved to be relatively dated and therefore heavily depreciated by the time of our analysis). The results are also not sensitive to dropping these cars (and their owners) from the sample.

Obtaining prices

Russia lacks an authoritative source of car price information analogous to the "Blue Book" in the United States. Instead, we relied upon prices listed on the two large auto-trading websites that were operating in Moscow during 2005 and 2006.

The first website (www.autonet.ru) contained online sales advertisements from various private owners and used-car dealers in Moscow and provided information on a large variety of makes, models and years of production. For the majority of cars in our sample we were able to find multiple matching offers (often more than 10), and we took the median asking price as the market value of the vehicle as of 2005. We also referred to the second website (www.automosk.ru which is no longer operating) to collect pricing data on the new vehicles in our sample. Whenever we could not find a price for a given combination of make, model, and production year, we used the most similar model available. For example, for 2003 Mercedes models 200 and 200E, we used the price of the 2003 Mercedes model 200D.

We use these data to estimate an exponential depreciation rate, as well as category-specific new-car premiums for seven classes of vehicles: 1) Luxury models, 2) German and Swedish cars, 3) Japanese cars, 4) American cars 5) other European (non-German or Swedish) cars, 6) Russian cars, and 7) Korean and Chinese cars (the full inventory of models and category assignments is available upon request).

To estimate category-specific new car premiums and the annual depreciation rate we employed the universe of about 1,043 car make/model/year prices we gathered from the on-line sites above, which contained information for the same make/model for different years.

Formally, let $X_{i,n}^{s,t}$ denote the price of a used car of make-model *i*, produced in year *s*, observed in year *t*. We assume that this price is given by

$$X_i^{s,t} = \bar{X}_i \exp\left\{-\delta(t-s) - \gamma_{k(i)} + \varepsilon_i^{s,t}\right\}$$

where $\bar{X}_i$ is the price of a new car of make model *i*, $\gamma_{k(i)}$ is the new car premium for the category into which make-model *i* falls, δ denotes the depreciation rate, and $\varepsilon_i^{s,t}$ is the error term. Taking logs, we obtain the regression model:

$$\ln X_i^{s,t} = \ln \bar{X}_i - \delta(t-s) - \gamma_{k(i)} + \varepsilon_i^{s,t} \quad (*)$$

We have information for the same car make/model *i* for different years, denote $t^*(i)$ the most recent year of observation for car make/model *i*. Denote $n^*(i)$ indicator for whether the price $X_i^{s,t^*(i)}$ we observed in this most recent year was for a new car (this implies $t^*(i)=s$ and no new car premium subtracted from the price).

Subtracting $\ln X_i^{s,t^*(i)} = \ln \overline{X}_i - \gamma_{k(i)}(1 - D(n^*(i) = 1)) - \delta(t^*(i) - s) + \varepsilon_{t^*(i),i}$ from equation (*) above we get:

$$\ln X_i^{s,t} - \ln X_i^{s,t^*(i)} = -\delta(t - t^*(i)) - \gamma_{k(i)}(D(n^*(i) = 1) + \tilde{\varepsilon}_i^{s,t},$$

which we estimate by ordinary least squares. The depreciation rate and category-specific new car premiums estimates are presented in Table A1.1. We also experimented with category-specific depreciation rates, but the results were very similar.

Table A2.1. Estimated new car premium and depreciation coefficients for different categories of cars

Variable	Coefficient	Std. Err.	t-value	P>t
New car premium				
Luxury	0.353	0.019	18.69	0.000
Russian	0.097	0.022	4.36	0.000
German	0.182	0.031	5.87	0.000
Japanese	0.111	0.024	4.59	0.000
American	0.076	0.046	1.66	0.098
Korean/Chinese	0.026	0.037	0.69	0.489
European	0.180	0.039	4.64	0.000
Depreciation for				
Each additional year	0.123	0.002	72.94	0.000

R-squared: 0.929, Number of observations: 1,043

For each car make/model in our data we find baseline price using car auction websites above. Then we use estimated depreciation rates and new car premiums estimated above to compute the estimated price $\hat{X}_{in}^{st}$ of all make-model-year combinations in our data, taking into account also if the car was purchased new or used.

Appendix 3. Sectoral breakdown of the data and comparisons between the data on classified versus unclassified employers (income sources)

In this appendix we compare our data on classified part of the Moscow workforce with the rest of the data and also present the details of the breakdown of the sample by sectors of economic activity.

As already mentioned (see Section III in the main text), the total number of observations in our data after the procedure described in Appendix 1 is 26,889,790, or about half of all raw entries in five income-tax databases. Among these, we identified the observation as that on a car owner in 1,604,231 cases (6 percent of total) by positively matching the individual in an income-tax database with his or her vehicle in the auto registry. The fraction of car owners seems to be lower than the official statistics, which put the car ownership rate in Moscow at about 20 percent in the late 1990s – early 2000s. Partly this is no doubt due to the difficulties involved in identifying potential matches but since there is no reason to suspect any systematic bias coming from bad data, we think that we have a representative sample of car owners in Moscow that probably comprise about a quarter of the population.

As also mentioned in Section III, we obtained classification of employers by ownership and sector of economic activity for the total of 13,613,869 observations, leaving 13,290,321 observations employed by entities whose ownership and sector of activity we don't know. Table A3.1 compares the number of observations on classified and unclassified employers sliced by the number of years for which the employer itself (as identified by the unique employer identification number) is present in the data.

Table A3.1. Classified and unclassified employers

	Number of observations in the data			
Years employer observed in data	Private	Government	Foreign	Unclassified
1	190,090	151,876	11,139	955,192
2	192,324	225,933	6,831	1,656,037
3	444,449	422,136	23,071	3,833,991
4	972,577	725,505	44,770	1,906,588
5	4,479,256	5,474,071	235,441	4,938,513
Total	6,278,696	6,999,521	321,252	13,290,321

As can be seen from Table A3.1, the employers we were able to classify by their ownership and sector of economic activity not only comprise more than half of all observations but they are also much more likely to be present in all five databases (ranging from 71.3 percent of the total for private firms to 78.2 percent for government entities and state-owned enterprises. Less than 3 percent of all observations on classified employers pertain to entities present on only one year. In contrast more than 7 percent of observations on unclassified employers (income-generating sources in the data) come from those observed in only one year and just about 37 percent survive for all five years. As explained in more detail in Section III of the main text, this means that we have successfully eliminated many paper companies that actually do not employ anybody but are simply a vehicle for tunneling and laundering money – a very serious problem in the Russian economy at the time and even today. Thus limiting the sample to only those employers we have been able to classify actually may be thought of increasing the representativeness of our estimations inasmuch as we are interested in real, not fake companies and their culture of transparency.

We have assigned sectors of economic activity to all classified employers by looking up their information from open sources. The list of the sectors and the breakdown of the sample (for all observations and separately for car owners) is shown in Table A3.2. In the analysis we drop observations on the "other" sector (which includes the self employed and employers whose sector of activity we were unable to classify even though we found their information and were able to determine ownership) as well as on private security firms (primarily because of difficulties in distinguishing real car ownership for consumption purposes from professionally required car ownership in this very specific sector of the Russian economy). We use the remaining 17 sector assignment dummies (less federal government, city and local government and law enforcement when we limit analysis to the private sector) in cross-section regressions to control for sector-specific differences in propensity to report earnings more or less transparently as well as other possible sector-specific factors that can affect our estimations.

Table A3.2 Sectors of economic activity

	All observations		*Car owners*	
Sectors	Number of observations	Fraction in total	Number of observations	Fraction in total
Banking, finance, insurance	1,398,132	10.27	121,368	14.93
Federal government	311,284	2.29	30,673	3.77
City and local government	256,657	1.89	13,683	1.68
Law enforcement	463,501	3.40	47,743	5.87
Higher education and research	1,420,080	10.43	75,184	9.25
Secondary education	604,329	4.44	22,927	2.82
Health care and medical services	905,089	6.65	47,923	5.89
Mass media	185,151	1.36	16,451	2.02
Construction	1,084,589	7.97	65,722	8.08
Utilities	658,756	4.84	27,658	3.40
Transportation	850,891	6.25	49,701	6.11
Wholesale and retail trade	1,120,370	8.23	68,463	8.42
Manufacturing	1,905,720	14.00	92,641	11.39
Sports and entertainment	259,967	1.91	14,351	1.77
Services	1,148,596	8.44	65,982	8.12
Communications, IT	416,218	3.06	23,264	2.86
Non-education not-for-profits	337,588	2.48	10,159	1.25
Private security	154,137	1.13	10,356	1.27
Other*	132,814	0.98	8,786	1.08

*Including self employed and unknown.

Table A.4: Additional Summary Statistics for Variables Used in Fixed-Effects Estimations
On "Stayers" in Foreign-Related Private Domestic Companies

	Private Domestic			State-Owned		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Car Income Gap	30,080	-15.323	2.611	57427	-15.150	2.423
Log Income	30,080	7.483	1.330	57427	7.287	1.056
Log Income (t+1)	10,102	7.571	1.490	22579	7.382	1.121
Log Car Value	30,080	7.982	0.839	57427	7.853	0.772
Log Car Value (t+1)	10,102	7.883	0.861	22579	7.751	0.804
Log Fraction Foreign	30,080	-5.943	1.285	57427	-7.466	1.061
Fraction foreign	30,080	0.006	0.016	57427	0.001	0.002
Change Log Fraction Foreign	13,073	0.210	0.565	28980	0.262	0.565
Percentile Distance	29,996	0.268	0.241	57418	0.288	0.248
Percentile Distance (last)	28,213	0.293	0.244	55410	0.276	0.232
Percentile Distance (car)	9,605	0.242	0.202	15560	0.281	0.207
Foreign mover above	30,080	0.366	0.482	57427	0.336	0.472
Maximum Foreign Mover Percentile	30,080	0.604	0.298	57427	0.527	0.294
Log # employees	30,080	7.362	1.322	57427	8.907	1.304
Own Percentile	30,080	0.748	0.215	57427	0.697	0.234
Mean Trust (country of registration)	30,080	23.745	0.238	57427	23.707	0.025
Mean Trust (citizenship, all)	30,080	23.700	0.002	57427	23.700	0.001
Mean Trust (citizenship, top 1%)	30,080	23.702	0.036	57427	23.701	0.006
Mean Trust (citizenship, top 5%)	30,080	23.701	0.010	57427	23.700	0.002
Mean Trust (citizenship, top 10%)	30,080	23.700	0.006	57427	23.700	0.002

Notes: Sample is limited to car-owners staying for at least two years in the same domestic private firm with a non-zero fraction of hires from multinationals, excluding those with market values of cars in the bottom 20 percent, with incomes not from employment, incomes below the minimum wage and above the equivalent of $100,000 in any given year, younger than 18 and older than 60.