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The effect of government corruption on the efficiency of US commercial airports ☆

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ABSTRACT

In this paper, we argue that the cost of providing public goods is affected by local government corruption because bureaucrats have no strong incentives to pursue mandated tasks under a corrupt environment. Commercial airports in the United States are chosen to demonstrate such impacts of corruption. We first develop a theory which predicts the impacts of corruption on productivity and variable input allocation of airports. We then test the predictions by estimating a stochastic variable cost frontier model which incorporates both technical and allocative efficiency of airports. The empirical evidence confirms the theoretical predictions by revealing the following: (1) airports are less productive in more corrupt environments; and (2) airports tend to use more contracting-out to replace in-house labor in more corrupt environments. The findings can be applied to the context of other public goods and have important policy implications for reforming governance structure of public good provision.

1. Introduction

This paper revisits a classical problem in public finance and urban economics – the efficiency of public goods. We interpret the provision of public goods by local governments as the following sequential decisions. Given a budget constraint, a local government first decides the target levels of public services such as public schools, transportation, health care, and public utilities. Second, capital and labor inputs are employed by the local government to achieve the target levels. The research questions regarding the efficiency of public goods may refer to: (1) whether or not the levels of different public goods are over- or under-provided; and (2) whether or not the expenditures on capital and labor inputs are minimized in producing the target levels of public goods. While scholars have directed a lot of attention to the first question – under- or over-provision of public goods,[1] this paper concentrates on the second issue – the cost of providing public goods. In particular, using commercial airports in the United States as an example, we investigate the effect of local government corruption on the cost of providing public goods.

Researchers have found that the cost of providing public goods is affected by factors including sources of funding (De Witte and Geys, 2011), competition and monitoring of voters (Grosskopf et al., 2001), centralized or decentralized public finance (Hoxby, 1999) and institutional arrangements (Oum et al., 2008). The effect of government corruption on the cost of providing public goods, however, has received limited attention. Corruption, which is defined as the misuse of public offices for private gains in Treisman (2000), affects economic development. Shleifer and Vishny (1993) point out that economic distortions caused by bribery, a major form of corruptions, are similar to those created by taxation. Moreover, corruption is illegal; therefore efforts to avoid detection and punishment make corruption more distorted and pernicious than taxation. Empirical findings support this argument. At the macro level, Mauro (1995, 1998) and Ades and Di Tella (1999) find a negative relationship between investment and corruption. At the micro level, Dal Bó and Rossi (2007) find that countries with higher corruption tend to have more inefficient electricity distribution firms. Empirical evidence in Fisman (2001), Svensson (2003), Clarke and Xu (2004), Di Tella and Schargrodsky (2003), Khwaja and Mian (2005), and Cai et al. (2009) show that corruption can divert firms' managerial efforts from productive activities to rent-seeking activities such as political connection building.

Motivated by the literature on the influence of corruption, in this paper we ask the question: Is the efficiency of local public

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[1] Under- or over-provision of local public goods is in general studied under the theory of fiscal federailism, which was formalized by Oats (1972). An excellent review of the theory can be found in Weingast (2009). The theory of fiscal federalism compares centralized and decentralized local public good provision. Institutional arrangement can also affect under- or over-provision of local public goods. Hoxby (2000) suggests that efficient spending decisions on local public goods could be achieved by private provision because of Tiebout sorting. Brueckner (1983) shows that efficient provision of public goods can be achieved by property-value maximizing local governments.

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sectors affected by corruption in the political environment? Answers to this question contribute to both the literature on the efficiency of public goods and the literature on the influence of corruption. Our study of this research question is based on the empirical findings from both political science and economics on the relationship between the accountability of public-policy making and corruption. Studies in Heywood (1997), Adserá et al. (2003), Alt and Lassen (2003), and Lederman and Loayza (2005) have identified the negative correlation between the accountability of public-policy making and the level of corruption.[2] Voters are not well informed about the policy outcomes when the accountability of public-policy making is low. As a result, the benefits for bureaucrats to pursue mandated tasks, which include the cost of providing public-goods, are low in a corrupt environment. We therefore hypothesize that the cost of providing public good is affected by corruption because bureaucrats have no strong incentives to devote efforts on mandated tasks under a corrupt environment.

We use commercial airports in the United States as an example to verify the above hypothesis. Commercial airports in the United States are operated by local governments either directly as government branches such as the Department of Aviation, or indirectly via airport authorities. As summarized in Wilson (1989), the US government branches have the following stylized facts: limited financial incentives because of public ownership, limited managerial autonomy because of the source of funding, and multiple objectives.[3] An airport authority is a not-for-profit public entity charged with the operation of an airport or a group of airports, and is in general financially self-sustaining.[4] Business decisions of an airport authority are made by the management led by a CEO, whose conduct is monitored by a board of directors appointed by county and city governments.

Airport efficiency is important to the economic performance of certain region. When an airport is publicly owned, a higher efficiency of it implies a lower budget burden to the local government. Moreover, through reductions of flight delays and various charges on both aeronautical and non-aeronautical services such as parking and concessions, a well managed airport reduces travel costs and hence facilitates air travel. Air travel has a significant positive effect on regional economies by boosting growth in population, employment, tourism, and income as documented in Brueckner (2003), Green (2007) and Blonigen and Cristea (2012). Empirical findings in Oum et al. (2008) and Craig et al. (2012) indicate that airport authorities are, on average, more efficient than airports operated as local government branches (or city-owned airports). Such findings are consistent with the theoretical findings in Dewatripont et al. (1999a) on the efficiency gain from being more focused on management missions, and can justify the policy practice of creating independent airport authorities to reform airport governance structure in the United States.

Since institutional arrangements are important to airport efficiency, corruption can affect airport efficiency through affecting institutional choices of airports. What is the effect of corruption on airport institutional choices? There are no clear-cut answers in theory to this question. As pointed out by Shleifer (1998), corruption has two conflicting consequences on government choices of ''in-house provision'' vs. ''contracting out'' of public services. On one hand, politicians can be in a better position to pursue political benefits when airports are kept in the hand of governments. On the other hand, contracting-out could be used by politicians to take private benefits (bribes) from providers. Reimer and Putnam (2009) show that the transfer of airport management from local governments to airport authorities in the United States can be attributed to various reasons including funding deficiency. In this paper, we focus on the channels via which corruption affects airport efficiency through affecting the decision-making of airports.

We first build a theoretical model to predict the impacts of corruption on the decision making of airports under the two institutional arrangements. We then test the theoretical predictions by using a unique data set consisting of 55 major airports from 30 states of the US during the period of 2001 to 2009. The corruption measure used in the empirical analysis is the state-level corruption index constructed by Glaeser and Saks (2006).[5] We find that corruption lowers productivity and increases the ratio of non-labor variable input to labor of airports; such impacts are different for airports under different institutional arrangements. In particular, our findings suggest that the efficiency gain of transferring airport management from local governments to independent airport authorities can only be achieved in environments with low corruption. Findings from this paper have important policy implications to improve the efficiency of public goods.

2. The theory

We first make the following general assumption based on the cited references in the introduction, and then outline the models on the decision-making of airports under the two institutional arrangements. The impacts of corruption on the decision-making of airports are discussed based on the general assumption.

General assumption: The accountability of public policy outcomes is lower in a more corrupt environment. Because voters are not well informed about public policy outcomes, the benefits for bureaucrats to devote efforts on mandated tasks are less in a more corrupt environment. As a result, bureaucrats have less incentive to pursue mandated tasks in a more corrupt environment.

The decision-making of an airport authority is modeled by a principal-agent model, which integrates three strands of literature: the theory in political economy on the goals of politicians (Kemp, 1991 and Kodrzycki, 1994), the career concern model on the incentive of managers (Holmstrom, 1982), and the agency theory of the firm (Jensen and Meckling, 1976). The decision-making of a city-owned airport is modeled as a career concern model with multiple tasks, a practice adopted by Dewatripont et al. (1999a,b) to model the decision-making of the US government branches. The impacts of government corruption on the decision-making of the two types of airports are discussed on the basis of the general assumption.

2.1. Model setup

We assume that an airport is required to meet an output target which is exogenously determined by air transport needs of the city and the region. We use $\bar{q}$ to denote the output target; as long as the actual output is not less than $\bar{q}$, the society cares only about the

[2] Explanations to the link between low accountability of public policy outcomes and high corruption include: 1. the politicians and bureaucrats are in a better position to pursue rent-seeking activities when the accountability of public policy outcomes is lower; and 2. in more corrupt environments, the politicians and bureaucrats are more likely to implement practices which reduce the accountability of public policy making in order to extract private benefits because the cost of doing so is less in more corrupt environments.

[3] For example, missions stated on the website of Chicago Department of Aviation, which administers the two major airports in Chicago, include the efficiency of airports, economic development of the region, and job creation.

[4] Daily operations of an airport authority are funded by the retained earnings of the airport.

[5] The corruption rate measures the number of public officials who were convicted for corruption by the Federal Justice Department every year for every 100,000 population. The rate is constructed by dividing the total number of federal convictions of public officials for public corruption from 1976 to 2002 by average population in the state in the same period. The corruption rate varies substantially across the states.

efficiency of the airport. We therefore model the production function of an airport as $q = (\bar{q} + e_p + \theta + \varepsilon_p) \cdot F(\bar{k}, l, m)$, where the total productivity depends on managerial efforts (e_p) in coordinating production process, managerial talent (θ) and a random noise representing productivity shock (ε_p). Managerial talent is a random variable and it is independent of the productivity shock. We further assume that $\theta \sim N(\bar{\theta}, \sigma_\theta^2)$ and $\varepsilon_p \sim N(0, \sigma_\varepsilon^2)$. Capital inputs are fixed at $\bar{k}$ in the short run and two variable inputs are labor (l) and non-labor variable inputs (m) including outsourcing services. In order to meet the output target, inputs at an airport are always set in the way that $\Pr(q \leqslant \bar{q})$ is very small for all e_p and θ .

As public entities, the US commercial airports are required to adopt the weight-based aviation charges for aircraft landings. Let τ denote the unit aviation charge ($ per seat), the measure of an airport's efficiency at the realized output is represented by the short-run profit function

$$\pi = \tau \cdot q - w_l \cdot l - w_m \cdot m \tag{1}$$

where w_l and w_m denote the unit prices of labor and non-labor inputs respectively (variable inputs prices are also assumed to be exogenously given to an airport). A low efficiency can result from either technical inefficiency which corresponds to an over-utilization of inputs given outputs and input mix, or allocative inefficiency which corresponds to a deviation of marginal rate of substitution from the ratio of variable inputs' prices.

2.2. Decision-making of airports under different institutional arrangements

Airport authorities. Decisions made by an airport authority are the equilibrium outcomes of the interaction between the principal (the board) and the agent (the manager). One main incentive for government to contract-out public services, as indicated by Savas (1987), Kemp (1991), Lopez-de-Silanes et al. (1997), is to get rid of budget burden, which is also the main incentive for local governments to transfer airport management to independent airport authorities, as summarized in Reimer and Putnam (2009). As a representative of the government, the board of directors of an airport authority cares the airport efficiency because a self-funding airport leads to lower public budgets. On the other hand, by appointing board members, local governments can still pursue political goals even after transferring airport management. Kemp and Kodrzycki point out that the main political goal pursued by politicians through public provision is to win supports of public employee unions. We assume here that the board of an airport authority still pursues the goal, or at least try to avoid active opposition from public employee unions. The way to model this objective is to define a threshold of non-labor to labor variable inputs ratio which is denoted by m_0/l_0. A positive deviation from the threshold, which is defined as $\tilde{m} \equiv \max\left\{0, \frac{m}{l} - \frac{m_0}{l_0}\right\}$ with m/l denoting the actual variable input ratio, generates disutility to the board. The utility function of the board is $\alpha \cdot \left(E(e_p + \theta + \varepsilon_p) - h(\tilde{m})\right) = \alpha \cdot (E(y_p) - h(\tilde{m}))$. In the utility function, $h(\tilde{m}) \geqslant 0$, $h(0) = 0$ and $h'(\cdot) \geqslant 0$; α captures the intensity of the board's preference for government objectives.

The manager of an airport authority, a not-for-profit entity, is motivated by career concerns; a high performance in managing airport operation raises labor market's perception of his ability and translates into future job opportunities. Since all information about the manager's talent is captured by $y_p \equiv e_p + \theta + \varepsilon_p$, the labor market can infer the manager's ability by observing the airport's productivity. The reward (R) to the manager is therefore $R = E(\theta|y_p)$.

With managerial autonomy, the manager can pursue efficiency through efficient allocation of inputs. However, career concerns do not offer the manager an incentive to allocate inputs efficiently because a more efficient allocation of inputs cannot signal the manager's ability to the labor market. What the manager could do with managerial autonomy is to pursue personal benefits through changing the allocation of inputs. Because of the low accountability of outsourcing, we model that the manager could use outsourcing to replace in-house labor in order to gain private benefits. The potential source of agency problems in our setting can be interpreted as a "pet project" that uses non-labor variable inputs (especially outsourcing) and generates benefits to the manager.

By costly monitoring, the board can push the manager toward the government objectives. We use γ to denote the units of monitoring. With more monitoring, the accountability of outsourcing transactions is higher such that private benefits generated from such transactions to the manager are less. The benefits from the pet project is denoted by $e_g g(\tilde{m}, \gamma)$ with e_g denoting the efforts spent on pursuing the pet project; $g(\tilde{m}, \gamma) \geqslant 0$ and $g(\tilde{m}, \gamma) = 0$ if $\tilde{m} = 0$, which basically state that the manager can gain positive benefits by deviating from government's target on non-labor to labor variable inputs ratio. We assume also that $\frac{\partial g(\tilde{m},\gamma)}{\partial \tilde{m}} > 0$, $\frac{\partial^2 g(\tilde{m},\gamma)}{\partial \tilde{m}^2} < 0$, $\frac{\partial g(\tilde{m},\gamma)}{\partial \gamma} < 0$, and $\frac{\partial^2 g(\tilde{m},\gamma)}{\partial \tilde{m} \partial \gamma} < 0$. The first two inequalities state that the benefits from the pet project are a strictly increasing and concave function of resource reallocation. The latter two inequalities state that the benefits and marginal benefits of the pet project are strictly decreasing with respect to the board's monitoring. The manager's expected utility function is $E(E(\theta|y_p)) + e_g g(\tilde{m}, \gamma)$. In the first term of the expected utility function, the inside expectation is with respect to talent and the outside expectation is with respect to productivity.

Given the monitoring from the board and market expectation for the manager's effort level e_p^e, the manager of an airport authority solves

$$\max_{e_p, e_g, \tilde{m}} E\left(E(\theta|y_p, e_p^e)\right) + e_g \cdot g(\tilde{m}, \gamma) - C_a(e_p + e_g) \tag{2}$$

$C_a(e_p + e_g)$ is the cost of the manager's (agent) total efforts. Taking the manager's response to monitoring into account, the board solves

$$\max_{\gamma} \alpha \cdot \left(E(y_p) - h(\tilde{m})\right) - C_b(\gamma) \tag{3}$$

where $C_b(\gamma)$ is the board's cost of monitoring. Both $C_a(e_p + e_g)$ and $C_b(\gamma)$ are assumed to be convex functions of efforts.

Local government branches. Because operations of an airport operated as a local government branch can be funded by local tax revenues and the funding sources restrict the airport's flexibility to change the allocation of inputs, we assume that the ratio between labor and non-labor variable inputs is exogenously given (determined by the public) at a city-owned airport.

As a bureaucrat, the manager of a city-owned airport pursues multiple tasks including airport efficiency. Let n denote the number of tasks pursued by the bureaucrat, the performance of task i (y_i) is determined by $y_i = e_i + \theta + \varepsilon_i$, where e_i denotes the effort spent on the task and ε_i represents the noise; $\varepsilon_i \sim_{iid} N(0, \sigma_\varepsilon^2)$ and talent (θ) is assumed to be the same for all tasks. The task of airport efficiency is then the one when $i = p$.

Timing of events in each period is as follows. First, the Constitution defines a measure of performance through which the bureaucrat's ability is evaluated. Second, the bureaucrat allocates efforts across multiple tasks. Third, talent and noises realize as random draws from their own distributions and the performances on the tasks are determined. Finally, the voters observe the performances $y \equiv (y_1, \ldots, y_n)$ and takes actions that result in reward to the bureaucrat. The reward function is $R(e_1, \ldots, e_n) = E(\theta|y)$. The cost of efforts is given by $C(e_1, \ldots, e_n) = C(e_1 + \cdots + e_n) = C(e)$ and the cost function is assumed to be a convex function of total efforts. Let

$e^e \equiv (e_1^e, \ldots, e_n^e)$ denote the public perception of the bureaucrat's effort levels, the problem faced by the bureaucrat is then to choose efforts to maximize his expected utility

$$\max_{(e_1,\ldots,e_n)} E(E(\theta|y, e^e)) - C(e) \quad (4)$$

2.3. Main results and predictions to guide empirical analysis

This section summarizes main results and makes predictions to guide the empirical analysis from the theoretical model. We omit the technical details and discuss only intuitions of these results. The detailed derivations to obtain the results can be found in the technical appendix of this paper.

We first look at the impacts of corruption on the decision-making of an airport authority based on the model in Eqs. (2) and (3). The optimal efforts and allocation of variable inputs to the manager, which are the solutions of Eq. (2), depend on both the job market's assessment on the manager's ability (the observation on y_p) and the board's monitoring level (γ). Corruption is not supposed to affect the job market's assessment on the manager's ability. However, because the benefits to the government by pushing the manger toward the goals of productivity increase and job creation are lower when outcomes of public policies are less informed to the voters, corruption could lower the board's preferences toward government goals (α). The optimal monitoring level to the board, which is the solution from Eq. (3), is lower when α is lower. Result 1 summarizes the decision-making of an airport authority and the impact of corruption on the decision-making.

Result 1:

(i) There exists a unique threshold of the board's monitoring level.
(ii) When the monitoring level from the board is greater than the threshold, the manager devotes all his effort to the productive activities of the airport and does not deviate from the government's target on the variable input ratio.
(iii) When the monitoring level from the board is lower than the threshold, the manager switches his effort from managing productive activities of the airport to pursue pet projects; in such case, the manager uses more outsourcing to replace in-house labor in order to gain more private benefits if the monitoring level is lower.
(iv) The monitoring level from the board is lower when the environment is more corrupt.

The decision-making of an airport operated as a local government branch is affected by the multiple task environment, as shown by Dewatripont et al. (1999b) and Alesina and Tabellini (2008). As for the impact of corruption on decision-making, the low accountability of public-policy outcomes in a corrupt environment implies that the voters are not well-informed about the performance of mandated tasks pursued by the bureaucrat who manages the airport. We model this by assuming that instead of observing y_i, the public can only observe $\tilde{y}_i = y_i + \eta_i$, where $\eta_i \sim_{iid} N(0, \sigma_\eta^2)$. The variance of η_i, which captures the noise associated with the voters' information on the performance of mandated tasks, affects the bureaucrat's total effort devoted to the mandated tasks and is larger when the environment is more corrupt.

Result 2:

(i) The manager of a city-owned airport devotes less total effort on the mandated tasks when the number of tasks increases (Dewatripont et al., 1999b).
(ii) The manager of a city-owned airport may misallocate his effort on the mandated tasks by focusing only on those which signal his ability to voters (Alesina and Tabellini, 2008).
(iii) The manager of a city-owned airport devotes less total effort on the mandated tasks when the environment is more corrupt.

The theoretical results enable us to draw several predictions which guide the empirical analysis in the next section. When we have a random sample of the US commercial airports from different states which vary in the corruption index constructed by Glaeser and Saks, the theoretical results suggest a negative correlation between the productivity of these airports and the corruption index. However, we expect that such a correlation is stronger in airport authorities than in airports operated as local government branches. The reason is that even in the absence of corruption, the productivity of city-owned airports can still be low because of the consequences of multiple task environment summarized in Result 2.

Prediction 1: Corruption affects productivity of airports negatively and such effect is stronger in airport authorities than in airports operated as local government branches.

We then predict the impacts of corruption on the allocation of variable inputs in airports. In the theoretical analysis, corruption will not affect resource allocation of a city-owned airport because the airport has little managerial autonomy in allocating inputs. For an airport authority, the theory predicts that a higher corruption leads to a lower monitoring effort from the board. The lower monitoring level in turn leads to a lesser managerial effort on improving airport productivity and a bigger managerial effort on pursuing private benefits via outsourcing.

Prediction 2: Corruption affects the ratio of non-labor to labor variable inputs in airport authorities positively.

The last prediction is on the comparison of productivity across institutional arrangements under different corruption environments. Airport authorities can only benefit from being focused when the board's monitoring effort is high, we hence have the following prediction.

Prediction 3: Airport authorities are more productive than airports operated as local government branches only in low corruption environments.

3. Empirical analysis

In this section, we first describe data used in the empirical analysis and then outline econometric models which test our theoretical predictions. Finally, we discuss identification issues faced by the analysis.

3.1. Data

The sample consists of a balanced panel of 55 US airports between 2001 and 2009. The data are compiled from various sources including Airport Council International (ACI), the U.S. Federal Aviation Authority (FAA), International Air Transport Association (IATA), and airport annual reports. Some data were obtained directly from the airports. Details on the data are provided in various issues of the ATRS Global Airport Benchmarking Report (for example, Air Transport Research Society, 2011).

In order to study the efficiency of airports, we need information on outputs, inputs, prices of variable inputs for each airport. We consider three output measures, namely the number of passengers, the number of aircraft movements (ATM) and revenues from non-aeronautical services including concessions, car parking, and numerous other services. These services are not directly related to aeronautical activities in a traditional sense, but are becoming increasingly more important for airports around the world and account for over 60% of total revenues of many airports. Variable inputs used by airports can be classified into three categories: (1) labor, measured by the number of (full time equivalent) employees who are on the airport operator's payroll; (2) purchased goods and materials; and (3) purchased services including outsourcing/contracting-out. In practice, few airports provide separate expense accounts for the purchased (outsourced) services and purchased goods and materials. Thus, we decided to combine (2) and (3) to form a so-called 'non-labor variable input". This non-labor variable input includes all expenses not directly related to capital or labor input costs. The price of labor input is measured by an average compensation per employee (including benefits). In addition to the variable inputs, two physical capital input indicators are considered: the number of runways and the total size of passenger terminal area measured in square meters.

Among the 55 airports, 28 are operated by local governments (city or state) and 18 are managed by an independent and autonomous management authority via a long term lease. Two airports (Nashville and Minneapolis-St. Paul) are 100% government corporation ownership and management and are grouped into the category of airport authority. Most airport authorities and public corporations were created much earlier than the time period covered by our study. Finally, seven airports are operated by port authorities, which are entities operating both seaports and airports.

The 55 airports are located in 30 states. The corruption index in Glaeser and Saks is calculated by using the number of government officials in a state convicted for corrupt practices through the Federal justice department and is represented as the corruption rate per capita for each state. We use this state-level corruption rate as the measure of the corruptive environment faced by the airports in our sample.[6] Table 1 lists the 55 airports, their institutional arrangements, the states where they are located, and the corruption rates of the states.[7]

Table 2 presents some summary statistics of the sample. These summary statistics indicate that there are large variations among the sample airports in the sample period (2001–2009) in terms of their size. For example, the annual passenger volume ranges from 2.2 million passengers to 83 million passengers. Labor cost shares range from 4% to 73%.

3.2. Econometric model

The empirical models are guided by the developed theory to test the impact of corruption on productivity and inputs allocation of airports under different institutional arrangements. For the purpose, we specify a short-run production cost function of airport i at time t as $C^*_{it}(Q_{it}, W^*_{it}, K_{it})$, where Q_{it} is the vector of outputs; W^*_{it} is the vector of variable inputs' shadow prices; and K_{it} is the vector of fixed capital inputs. We include three outputs in vector Q_{it} (number of aircraft movements q_{1it}; number of passengers q_{2it}; and non-aeronautical output q_{3it}), two variable input prices in vector W^*_{it} (labor price w^*_{1it} and non-labor variable input price w^*_{2it}), and two fixed capital inputs in vector K_{it} (number of runways k_{1it} and terminal size k_{2it}).

The observed actual production cost, which is denoted by $C_{it}(Q_{it}, W^*_{it}, K_{it})$, can deviate from the cost frontier because of technical and allocative inefficiency. In order to model allocative efficiency, we follow Atkinson and Cornwell (1994) and Kumbhakar and Tsionas (2005) to let shadow prices of variable inputs parametrically relate to their market prices ($W_{it} \equiv (w_{1it}, w_{2it})$) such that $W^*_{it} \equiv (w^*_{1it}, w^*_{2it}) = (\lambda_1 w_{1it}, \lambda_2 w_{2it})$, where $\lambda_1, \lambda_2 > 0$. The allocative efficiency is measured then by the parameter vector $\lambda \equiv (\lambda_1, \lambda_2)$ and an airport is allocatively efficient if $\lambda_1/\lambda_2 = 1$. $\lambda_1/\lambda_2 < 1$ implies the over-utilization of labor input relative to non-labor variable inputs and $\lambda_1/\lambda_2 > 1$ implies the relative over-utilization of non-labor variable inputs.

As for technical inefficiency, we let $x^*_{jit}(Q_{it}, W^*_{it}, K_{it})$ denote the conditional demand function of variable input j and j = 1, 2. The actual variable input (x_{jit}) can be inflated by technical inefficiency and we specify $x_{jit} = \exp(\Delta_i) \cdot x^*_{jit}(Q_{it}, W^*_{it}, K_{it})$, in which $\exp(\Delta_i)$ captures overutilization of inputs given outputs and inputs mix caused by technical inefficiency. By Shephard's lemma we express the actual variable cost as

$$\begin{aligned} C_{it}(Q_{it}, W^*_{it}, K_{it}) &= \exp(\Delta_i) \cdot \sum_{j=1}^{2} w_{jit} x^*_{jit}(Q_{it}, W^*_{jit}, K_{it}) \\ &= \exp(\Delta_i) \cdot \sum_{j=1}^{2} w_{jit} \frac{\partial C^*_{it}(Q_{it}, W^*_{it}, K_{it})}{\partial w^*_{jit}} \\ &= \exp(\Delta_i) \cdot \sum_{j=1}^{2} w_{jit} \frac{\partial \ln C^*_{it}(Q_{it}, W^*_{it}, K_{it})}{\partial \ln w^*_{jit}} \\ &\quad \times \frac{C^*_{it}(Q_{it}, W^*_{it}, K_{it})}{w^*_{jit}} \\ &= C^*_{it}(Q_{it}, W^*_{it}, K_{it}) \cdot \exp(\Delta_i) \cdot \sum_{j=1}^{2} \frac{S^*_{jit}}{\lambda_j} \end{aligned} \tag{5}$$

where S^*_{jit} is the shadow share of variable input j; $\exp(\Delta_i)$ measures the deviation from the cost frontier caused by technical inefficiency and $\sum_{j=1}^{2} S^*_{jit}/\lambda_j$ measures the deviation from the cost frontier caused by allocative inefficiency.

Eq. (5) leads to the following empirical cost equation

$$\ln C_{it} = \ln C^*_{it}(Q_{it}, W^*_{it}, K_{it}) + \ln\left\{\sum_{j=1}^{2} \lambda_{ji}^{-1} S^*_{jit}\right\} + \Delta_i + \varepsilon^c_{it} \tag{6}$$

where ε^c_{it} represents noises associated with cost observations.By definition, the actual labor share is $S_{1it} = w_{1it}x_{1it}/C_{it} = w_{1it}\exp(\Delta_i)x^*_{1it}/C_{it}$ and the shadow labor share is $S^*_{1it} = \lambda_{1i} w_{1it} x^*_{1it}/C^*_{it}$. Combining these two equations with Eq. (6), we have the following observed labor share equation.

$$S_{1it} = \frac{\lambda_{1i}^{-1} S^*_{1it}}{\sum_{j=1}^{2} \lambda_{ji}^{-1} S^*_{jit}} + \varepsilon^s_{it} \tag{7}$$

The random term ε^s_{it} represents measurement error to the labor share equation. Efficiency of parameter estimates to the cost equation can be improved by incorporating variable inputs' share equations. Since we have only two variable inputs, in order to avoid the singularity problem, we chose to use the labor share equation only.[8]

Eqs. (6) and (7) are treated as a system of non-linear equations with panel data. We use a random-components specification to account for autocorrelation in error terms caused by the panel structure of the data. The random-components specification takes the following form[9]:

[6] This paper focuses on state level corruption issues. Compared to the country-level corruption index, this state-level corruption measure is more objective because country-level corruption index is constructed via subjective survey evidence.

[7] A corruption rate of 0.23 (for CA) means that 0.23 public officials who were convicted for corruption every year per every 100,000 population.

[8] The empirical results are invariant to the choice of either labor cost share equation or other variable input cost share equation.

[9] This specification employs the prior knowledge that the variance of log cost is greater than the variance of labor share. If $\mathrm{var}(\varepsilon^c_{it}) < \mathrm{var}(\varepsilon^s_{it})$, it is better to specify $\varepsilon^c_{it} = \omega_i + \xi^c_{it}$ and $\varepsilon^s_{it} = \mu_i + \omega_i + \xi^s_{it}$.

Table 1
List of Airports.

Airport code	State	Institutional arrangement	Year that airport authority/corporation were created	State corruption rate[a]
ABQ	NM	City government	–	0.263
ALB	NY	Airport authority	1993	0.439
ATL	GA	City government	–	0.373
AUS	TX	City government	–	0.209
BNA	TN	Public corporation	1970	0.464
BOS	MA	Port authority	–	0.240
BWI	MD	City government	–	0.230
CLE	OH	City government	–	0.341
CLT	NC	City government	–	0.170
CVG	IN	Airport authority	1943	0.190
DCA	DC	Airport authority	1987	0.329 [b]
DEN	CO	City government	–	0.151
DFW	TX	Airport authority	1968	0.209
DTW	MI	Airport authority	2002	0.181
EWR	NJ	Port authority	–	0.273[c]
FLL	FL	Airport authority	1948	0.368
HNL	HW	State government	–	0.295
IAD	VA	Airport authority	1987	0.329
IAH	TX	City government	–	0.209
IND	IN	Airport authority	1962	0.190
JAX	FL	Airport authority	2001	0.368
JFK	NY	Port authority	–	0.439
LAS	NV	City government	–	0.222
LAX	CA	City government	–	0.232
LGA	NY	Port authority	–	0.439
MCI	MO	City government	–	0.248
MCO	FL	Airport authority	1975	0.368
MDW	IL	City government	–	0.458
MEM	TN	Airport authority	1969	0.464
MIA	FL	City government	–	0.368
MKE	WI	City government	–	0.150
MSP	MN	Public corporation	1943	0.121
MSY	LA	City government	–	0.513
OAK	CA	Port authority	–	0.232
ONT	CA	City government	–	0.232
ORD	IL	City government	–	0.458
PBI	FL	City government	–	0.368
PDX	OR	Port authority	–	0.074
PHL	PA	City government	–	0.361
PHX	AZ	City government	–	0.158
PIT	PA	Airport authority	1999	0.361
RDU	NC	Airport authority	1939	0.170
RIC	VA	Airport authority	1975	0.329
RNO	NV	Airport authority	1977	0.222
SAN	CA	Airport Authority	2003	0.232
SAT	TX	City government	–	0.209
SDF	KY	Airport authority	1928	0.333
SEA	WA	Port authority	–	0.104
SFO	CA	City government	–	0.232
SJC	CA	City government	–	0.232
SLC	UT	City government	–	0.130
SMF	CA	City government	–	0.232
SNA	CA	City government	–	0.232
STL	MO	Airport authority	1968	0.248
TPA	FL	Airport authority	1945	0.368

[a] The corruption rate measures the number of public officials who were convicted for corruption every year for every 100,000 population. The rate is constructed by dividing the total number of federal convictions of public officials for public corruption from 1976 to 2002 by average population in the state in the same period.
[b] There is no corruption rate for DC in Glaeser and Saks (2006). The two airports, DCA and IAD (which is located in Virginia), are operated by the same airport authority. We therefore use the corruption rate of Virginia for DCA.
[c] The Newark airport (EWR) has the same ownership as the two NYC airports – JFK and LGA. Although corruption rates in New Jersey and New York are different, we assume that the three airports face the same corruption environment. In estimation, we use the corruption rate of New York for the three airports.

$$\varepsilon_{it}^c = \mu_i + \omega_i + \xi_{it}^c \text{ and } \varepsilon_{it}^s = \omega_i + \xi_{it}^s \tag{8}$$

where $\mu_i, \omega_i, \xi_{it}^c$ and ξ_{it}^s are random components (with zero mean) which are independent with each other. Specification in (8) allows error terms from the same airport to be correlated with each other and the correlation within the cost equation is different from the correlation within the labor share equation; the cross-equation correlation is captured by the common random component ω_i. Let $e_i \equiv (\varepsilon_{i1}^c, \varepsilon_{i2}^c, \ldots, \varepsilon_{iT}^c, \varepsilon_{i1}^s, \varepsilon_{i2}^s, \ldots, \varepsilon_{iT}^s)'$ denote the vector of errors of airport i, we have

$$Var(e_i) = \begin{bmatrix} \Sigma_{cc} & \Sigma_{cs} \\ \Sigma_{cs} & \Sigma_{ss} \end{bmatrix}_{2T \times 2T} \tag{9}$$

where the diagonal and off-diagonal elements in Σ_{cc}, which is the variance–covariance matrix of error terms of cost equation, are $\text{var}(\mu_i) + \text{var}(\omega_i) + \text{var}(\xi_{it}^c)$ and $\text{var}(\mu_i) + \text{var}(\omega_i)$ respectively; the diagonal and off-diagonal elements in Σ_{ss}, which is the variance–covariance matrix of error terms of labor share equation, are $\text{var}(\omega_i) + \text{var}(\xi_{it}^s)$ and $\text{var}(\omega_i)$ respectively; and the elements in Σ_{cs}, which is the covariance matrix between cost errors and

Table 2
Summary statistics of airport data.

Variables	Mean (standard error) or fraction in the sample
Output measures	
Number of Passengers (million US $ per year)	22 (18)
Number of Aircraft Movements (000's per year)	304 (197)
Non-Aeronautical Revenue (000's PPP deflated $ per year)	76 (55)
Variable inputs	
Number of Employee	577 (499)
Non-labor Variable Cost (million US $ per year)	63 (53)
Fixed inputs	
Number of Runways	3.37 (1.23)
Terminal Size (000's Squared Meter)	186 (161)
Variable inputs' prices	
Wage Rate (000's US $ per year)	83 (59)
Variable input's share	
Labor Cost Share	0.39 (0.14)
Number of Observations	495

labor-share errors, are var(ω_i). As we will see later, our GMM estimation procedure, which does not rely on any distribution assumptions on the error components, accounts for the correlation structure in (9) explicitly.

In the equations, the size of Δ_i measures technical efficiency of airport *i*. Because only the ratio $\lambda_i \equiv \lambda_{1i}/\lambda_{2i}$ can be identified, we normalize $\lambda_{2i} = 1$ in estimation and the estimates of λ_i measure allocative efficiency of airports. In order to restrict λ_i to be non-negative, we further specify $\lambda_i = \exp(o_i)$. Our research question is to identify the effects of corruption on both Δ_i and o_i under different institutional arrangements.

3.3. Identification and estimation

The specified econometric model hypothesizes that airport efficiency, both technical and allocative, is affected by corruption and such impacts are different for airports under different institutional arrangements. In order to test empirically such hypotheses, we compile data from 55 US airports with different institutional arrangements. The 55 airports are from 30 states which vary in the corruption index. Empirical identification on the relationship between airport efficiency and institutional arrangements/corruption relies on such variation in data, hence faces several challenges.

The first identification issue is that institutional arrangements of airports may be endogenous. Local governments may strategically transfer management of efficient or inefficient airports to independent authorities. Our statistical inference would be biased in such cases. However, Lopez-de-Silanes et al. (1997) show that political factors are the most important determinants of local governments' decisions on in-house provision vs. contracting out public services. These political factors include support from public employee unions, job creation in public sectors, and tax burden. By reviewing cases of airport management transfers from local governments to airport authorities, Reimer and Putnam (2009) find that funding deficiency of individual airports has often been the most common reason for such transfers. Finally, as shown in Table 1, institutional arrangements of most airports in the sample are predetermined to our analysis. If an airport authority was created long time ago, the decision is unlikely to be correlated with random shocks to the efficiency of the airport during the sampling period of 2001–2009. We estimate the empirical model using both the full sample and the subsample excluding airports with institutional change after 1990. The change in estimation sample does not alter results significantly. Some airports in our sample are operated by the port authorities just because they are located close to major seaports with long history and operated by powerful port authorities. Unlike an airport authority which operates local airport(s) only, a port authority operates both local sea port(s) and local airport(s). We therefore conclude that endogeneity in airport institutional arrangement does not pose any serious problem to the identification.

The second identification issue is that many airports' characteristics, which are beyond managerial control, affect also efficiency of airports. Without a proper control for such characteristics, Δ_i in Eq. (6) captures the effect of the omitted characteristics on airport efficiency. Our empirical strategy to address this identification issue is to construct a set of control variables, which is denoted by Z_i, to capture the impact of airport characteristics on airport efficiency. The first set of control variables in Z_i includes those measuring differences in airports' technology. Airports in the data include those like San Francisco International Airport (SFO) which serves a large volume of international passengers and those like Santa Ana Airport (SNA) which serves mainly domestic passengers. Serving international passengers requires additional spaces (for example, immigration and customs) which may affect costs of airports. We therefore construct the percentage of international passengers for each sampled airport. Similarly, serving passengers and serving air cargo require different technologies and we use the percentage of cargo traffic to control for airport heterogeneity in that dimension. Several airports such as Chicago O'Hare (ORD) Airport in the data are the hubs of major airlines. At the hubs, airlines' operations involve lots of hubbing activities which boost both the number of scheduled flights and the number of connecting passengers. Since hub airports are expected to have different production technologies from spoke airports, we include the hub airport dummy to capture such differences.

Airports in the sample face different natural conditions and market characteristics which in turn affect airports' operations. We use the average temperature in January, the average temperature difference between January and July, and the tourist city dummy, the population of Metropolitan Statistical Area (MSA), the median MSA household income, and a dummy variable indicating whether there exist multiple major airports in the MSA to control for different natural conditions and market characteristics faced by the airports. Because there are more than one airport in the sample in large metropolitan areas of San Francisco Bay Area, Los Angeles, New York City, Washington, DC, and Chicago, we include dummies of these metropolitan areas in order to capture possible group effects in airports' operations.

The corruption measure in the empirical model is at the state level. Operating costs of airports may be affected by state characteristics which affect also corruption. We include a set of control variables which measure state characteristics in Z_i. These variables are used by Glaeser and Saks (2006) in their study to identify causes to state corruption and are compiled from the Report on Economic Freedom published by Clemson University. The state level control variables include tax revenue per capita, the percentage of public employee salary in state GDP, the density of public employee in state population and the education level of state residents. We include further state dummies to capture possible group effects of airports which are located in the same state. Table 3 presents all control variables along with their definitions. We incorporate these control variables into the empirical cost equation in (6) to have

$$\ln C_{it} = \ln C^*_{it}(Q_{it}, W^*_{it}, K_{it}) + \ln\left\{\sum_{j=1}^{2} \lambda_{ji}^{-1} S^*_{jit}\right\} + Z_i\Gamma + \Delta_i + \varepsilon^c_{it} \qquad (6')$$

The third identification issue is that outputs of an airport could be endogenously determined if the airport could price strategically.

Table 3
List of control variables for airport heterogeneity.

Variables	Description
% of international passengers	
% of cargo output	Measured in terms of Work Load Unit (WLU), a commonly used output measure in the aviation industry that combines passenger and cargo traffic volume. One WLU is defined as one passenger or 100 kg of cargo
Average temperature in January	
Average temperature difference between January and July	
MSA population	From the 1990 Census
MSA average household income	From the 1990 Census
Tourist city dummy	1 if in Nevada or Florida
Hub airport dummy	We define following hubs in the US markets: Chicago-O'Hare (American. United), Cleveland (Continental), Newark (Continental), Atlanta (Delta), San Francisco (United), Dallas-Ft. Worth (American), Philadelphia (US Airways), Phoenix (US Airways), Detroit (Northwest), St. Louis (American), Houston (Continental), Washington-Dulles (United), Minneapolis-St. Paul (Northwest), Cincinnati (Delta), Salt Lake City (Delta), Denver (United), and Miami (American)
Tax per capita of state in 1992	Compiled from the Report on Economic Freedom published by Clemson University
Ratio of public vs. private sector salary of state in 1992	Compiled from the Report on Economic Freedom published by Clemson University
Population of state	From the 1990 Census
Income per capita of state	From the 1990 Census
% with 4+ years of college education of state	From the 1990 Census
Multiple airports	1 if there are multiple commercial airports in the metropolitan area
NYC	
Washington, DC	
Chicago	
San Francisco	
Los Angeles	
Miami	
Texas	
Florida	
Indiana	
Missouri	
North Carolina	
Nevada	
Pennsylvania	
Tennessee	
Western states	Western states include: AZ, CA, CO, HW, NV, OR, WA, and UT
Eastern states	Eastern states include: DC, FL, GA, KY, MA, MD, NC, NJ, NY, PA, TN, and VA

For example, facing a positive shock on ε_{it}^{c}, that is, an unexpected increase in operation costs, an airport can potentially increase its charges to transfer part of the cost increase to airport users. In this case, ε_{it}^{c} is correlated with output measures in the cost equation. However, as public entities, US commercial airports have to stick to the Federal aircraft-weight-based aviation charges such that the endogeneity of output measures does not pose a serious concern to the identification.

Identification to the stochastic cost frontier system relies on a parameterization for the cost frontier. Because the cost function in (5) can be more conveniently estimated by taking log, as shown in Eq. (6), we choose to use the translog functional form to approximate the log cost frontier. The labor share equation in (7) can be easily derived from the translog cost frontier. Under another popular parameterization – the Generalized Leontief function, the functional form of the cost equation, which incorporates both technical and allocative efficiency, would be very complicated. We use a nonparametric approach – variable factor productivity regression, to test the robustness of our findings to the model specification.

Finally, identification to the stochastic cost frontier system faces the so-called incidental parameter problem if Δ_i and o_i are specified as individual dummies, because identification for each of these dummies relies on only nine observations (because we have panel data from 2001 to 2009). One way to overcome this problem is to specify Δ_i and o_i as random variables whose distributions are parameterized with limited number of parameters. However, identification under such a random effect specification relies on strong assumptions on the independence between Δ_i and o_i and between the random effects and the regressors. Because our research question is about the effects of corruption on airport efficiency under different institutional arrangements rather than about measuring individual airports' efficiency levels, in the baseline estimations we specify

$$\Delta_i = X_i B \text{ and } o_i = X_i B \tag{10}$$

where X_i is the vector of institutional arrangements along with their interactions with corruption.

In sum, our baseline empirical specification consists of two nonlinear equations – Eqs. (6′) and (7), in which Δ_i and o_i are specified as in Eq. (10). As a robustness check, we compare the baseline estimation results with ones from a two-step approach in which Δ_i and o_i are specified as airport dummies in Eqs. (6) and (7); the estimated Δ_i and o_i are used as dependent variables to run regressions on Z_i and X_i .

Parameters in the empirical cost equation and labor share equation are estimated by an efficient Generalized Method of Moments (GMM) approach, in which the moment conditions are the orthogonal conditions

$$E(\varepsilon_{it}^{c}|V_{it}) = E(\varepsilon_{it}^{s}|V_{it}) = 0 \tag{11}$$

where V_{it} is a set of instruments including all regressors. The GMM estimation is efficient because the weighting matrix used in estimation accounts for the correlation among errors from the same airport as specified in Eq. (9). Details of the estimation are contained in the technical appendix of the paper.

4. Empirical results

We now turn our focus to the empirical models which investigate whether corruption affects airport efficiency by influencing

Table 4
Estimations results of the stochastic frontier model.[a]

Coefficients	(1) Full sample	(2) Drop airports with institutional change after 1990; drop observations before 2003 or after 2008
Panel A: Allocative efficiency parameters		
City	−2.6007*** (0.9127)	−2.0727*** (0.8002)
Airport authority	−2.8249*** (0.9289)	−2.3920*** (0.8345)
Port authority	−2.3666*** (0.9196)	−1.9241*** (0.7837)
City × Corruption	1.4491*** (0.4882)	1.5228*** (0.5330)
Airport authority × Corruption	1.5428*** (0.4507)	1.8366*** (0.6588)
Port authority × Corruption	2.8571*** (0.5289)	2.9105*** (0.7738)
Panel B: Technical efficiency parameters (city-owned airports are the base)		
Airport authority	−0.7813*** (0.2491)	−1.0314*** (0.3719)
Port authority	−0.0426 (0.2092)	0.6244*** (0.3151)
City × Corruption	1.0518*** (0.4749)	2.3980*** (0.9367)
Airport authority × Corruption	3.2182*** (0.6974)	5.5794*** (1.3974)
Port authority × Corruption	1.1612*** (0.5154)	0.7112 (0.5838)
Panel C: Cost structure parameters		
Short-run cost elasticity of aircraft movements	0.0832 (0.1303)	0.1748** (0.1021)
Short-run cost elasticity of number of passengers	0.1918** (0.1122)	0.1535 (0.1035)
Short-run cost elasticity of non-aeronautical revenue	0.3286*** (0.0752)	0.1953*** (0.0853)
Predicted shadow labor share	0.1013** (0.0534)	0.1342*** (0.0632)
Short-run cost elasticity of number of runways	0.1846*** (0.0887)	0.1622*** (0.0669)
Short-run cost elasticity of terminal size	0.0312 (0.0682)	0.0152 (0.0472)
Number of airports	55	50
Number of observations	495	300

[a] Numbers in parentheses are the GMM standard errors using the optimal weighting matrix (details can be found in the technical appendix of the paper). Year fixed effects and control variables listed Table 3 are included in all estimations. All elasticities are evaluated at the sample mean of variables.
*** Significant at 5% level.
** Significant at 10% level.

airports' decision-making. Table 4 presents the estimation results from the baseline specification. Since 1990, five airports in our data have been transferred from local governments to airport authorities. We drop those five airports in model 2 to make sure that institutional arrangements of airports are predetermined in the estimation. We also drop observations before 2003 and after 2008 in model 2 to exclude the short-run impacts of the event of 9/11 and the 2008 financial crisis.

Taking the usual practice to estimate translog cost system, we impose the symmetric and homogeneity constraints in the estimations.[10] Because it is difficult to interpret directly the results of the second order terms in a *translog* function, in the last panel of Table 4 we report the cost elasticities with respect to the three outputs and quasi fixed inputs, as well as the predicted shadow labor variable input. The positive cost output elasticities and predicted shadow labor share imply that monotonicity conditions in outputs and input prices are satisfied. A well-defined variable cost frontier should also be concave with respect to variable input shadow prices, which requires that the Hessian matrix of the variable cost frontier with respect to the shadow prices of inputs is negative semi-definite. We do not impose this condition in estimation. The estimated coefficient of the square term of labor shadow price has a positive sign and therefore violates the concavity requirement.[11] However, the magnitude of this coefficient is very small (between 0.008 and 0.01 across models) and is not statistically significant.

The estimates of the cost output elasticities across models suggest that on average the airports exhibit economies of scale in the short run. We find evidence of slight over-capitalization in the airports, as indicated by the small but positive cost elasticity of number of runways.[12] The predicted shadow labor share is substantially less than the observed labor share (about 0.39). Such a finding suggests that on average the airports over-utilize labor inputs relative to non-labor variable inputs.

4.1. Allocative and technical efficiency parameters

The first two panels of Table 4 present estimation results of the allocative and technical efficiency parameters. The following findings are robust across the models. First, all airports tend to use more contracting-out to replace in-house labor in a more corrupt environment; such impact of corruption on variable inputs' allocation is the strongest in airports operated by port authority. Second, in the absence of corruption, airport authorities are on average more technically efficient than city-owned airports. Third, corruption rate has a negative impact on productivity of airports such impact is especially strong for airport authorities. Finally, in the absence of corruption, all airports over-utilize labor relative to non-labor variable inputs, as indicated by the negative values of the three coefficients of institutional dummies in the first panel on the allocative efficiency parameters (because $\lambda_i < 1$).

We run different robustness checks to the findings from the baseline estimations. In the first set of robustness checks, we change the model specification by specifying both $\varDelta_i$ and o_i in Eq. (6) and (7) as airport dummies. Their estimates, which are denoted by $\widehat{\varDelta}_i$ and $\hat{o}_i$ from the GMM estimation, are used as dependent variables to formulate the second stage regressions $\widehat{\varDelta}_i = \alpha + Z_i\Gamma + X_iB + \mu_{1i}$ and $\hat{o}_i = X_iB + \mu_{2i}$, where X_i are defined in Eq. (10) and Z_i is the vector of control variables for airport heterogeneity. Results from the second-stage regressions, which can be found in the appendix, are quite consistent with the baseline results.

The second set of robustness checks serves the purpose of testing sensitivity of our findings to the cost frontier parameterization. We construct the variable factor productivity for each airport in each year. The three outputs and two variable inputs are

[10] Please see the appendix for details.
[11] Please see Diewert and Wales (1987) for details.
[12] Bottasso and Conti (2012) find over-capitalization in large UK airports. Our finding is consistent with theirs because the 55 airports in our data are the major commercial airports in the US.

aggregated by multilateral translog index which is proposed by Caves et al. (1982). We then run regressions of the constructed variable factor productivity on the institutional dummies along with their interactions with the corruption rate after controlling for airport heterogeneity measured by the variables listed in Table 3. The results, which can be found in the appendix, show that the variable factor productivity of airport authorities is significantly higher than that of city-owned airports in the absence of corruption and corruption reduces the variable factor productivity of airport authorities significantly.

4.2. Interpretation of empirical findings

The empirical findings are in general consistent with the theoretical predictions. The only exception is that the theory predicts no impacts of corruption on resource allocation of city-owned airports, which are assumed to have no autonomy to allocate resources. Our empirical results indicate that the management of city-owned airports, similar to that in airport authorities, is likely to exploit personal benefits via changing the allocation of inputs under a highly corrupt environment. The identified agency problem of city-owned airports under corrupt environments can in fact have intuitive interpretation under our theoretical framework; i.e., the low accountability of public policy outcomes in a highly corrupt environment leads to a low monitoring of bureaucrats' behavior by the voters, and as such, the bureaucrat can have certain degree of autonomy to exploit the allocation of inputs to his personal benefits.

Corruption affects the productivity of port authorities, which have similar internal organization as airport authorities; the lower monitoring efforts from the board in a more corrupt environment induce lesser efforts of the manager on productive activities. The impacts of corruption on productivity in port authorities are not as strong as in airport authorities because port authorities manage multiple transport facilities with multiple tasks. Productivity of port authorities could be low even in the absence of corruption, a case similar to that of city-owned airports. Corruption affects port authorities the most on allocation of variable inputs because the authorities have managerial autonomy and operate more complicated business, a fact which leads to a lower accountability of resource allocation than in the case of airport authorities.

4.3. Limitations of the empirical analysis

Empirical analysis of the paper is based on a relatively small sample, an annual panel of 55 airports for 9 years. Also, the analysis is restricted to airports in the United States. It would be interesting to know if the findings of this study can be applied to other countries, different continents, and/or worldwide airports. Another limitation of our analysis is the use of physical capital stocks – terminal size and number of runways – as proxy measure of capital inputs of airports. Such measures cannot capture the effects of either "pork" spending on airports or the gold plating lounges and other facilities. Such spending is particularly important for airport efficiency studies. Future research on that topic is well advised to consider alternative measures for capital inputs such as capital stock measures constructed by investment flow data.

In a recent paper, Yan and Winston (2014) show that privatization can create a competitive airport market in metropolitan areas served by multiple commercial airports such as in San Francisco and New York. Airport inefficiency caused by government corruption could be offset by airport competitions. In this paper, we use a dummy variable which indicates the existence of multiple commercial airports in a metropolitan area to capture the possible effects of airport competition on efficiency. The coefficient of the dummy variable is not statistically significant in all models. However, such result cannot be interpreted as the evidence that airport competition has no significant effects on airport efficiency, because under public ownership, the US commercial airports have no freedom to charge strategically to compete with each other. Airport inefficiency caused by government corruption could also be offset by competition among transport modes. Behrens and Pels (2012) and Fu et al. (2014) document air-rail competition in intercity markets of Europe and Japan respectively. The relationship between airport efficiency and market competition, both within and across transport modes, can be an interesting question for future research.

5. Conclusions

Findings from the airport context in this paper can be generalized to the context of other local public services. In general, the efficiency of providing local public services under public ownership is expected to be affected negatively by government corruption because a corrupt environment discourages bureaucrats to devote efforts on mandated tasks. Moreover, as in the case of transferring airport management from local governments to airport authorities, simply creating mission-focused agencies as a way to reform governance structure with the purpose of improving the efficiency of providing local public services would not work well under corrupt environments; corruption would lower monitoring efforts of governments and in turn the lowed monitoring efforts would lead to severe agency problems in providing local public services.

In sum, due to the low accountability of public policy making, managerial efforts of public sectors in a corrupt environment could be reduced and/or diverted away from productive activities. Therefore the first lesson from the airport context is that policies which increase the accountability of public policy outcomes can improve the efficiency of public services in a corrupt environment. The second lesson from the airport context is that governance structure of local public sectors, which can lead to an efficient provision of public services even in a corrupt environment, should not only offer managers strong incentives to manage productive activities and exploit efficient input allocation, but also insulate managerial decisions from political influence. In this regard, privatization should receive more attention in reforming governance structure of local public sectors.[13]

Appendix A

The appendix describes the technical details of the theoretical models and empirical estimation in the text.

A.1. Technical derivation of result 1

This section derives formally result 1 in the text. We first characterize the manger's equilibrium efforts given a monitoring level from the board. Because the manager's efforts on the productive activity and on the pet project are not separable, we can divide the discussion into two situations – to pursue and not to pursue the pet project. When the manager of an airport authority does not pursue the pet project (i.e.$e_g = 0$), the manager chooses efforts spent on productivity activities (e_p) given a market's expectation

[13] The US congress created an Airport Privatization Pilot Program in 1996, but the program is making a very slow progress in reforming airport governance structure. In other contexts such as utilities and highways, policymakers have sought the private sector's assistance to provide local public services by forming so-called public–private partnerships (PPPs), where the government leases a service to a private investor(s) for a specified period and the investor(s) earns an acceptable rate of return.

Table A1
Robustness checks: estimation results from the second-stage regressions.[a]

	(1) Full sample	(2) Drop airports with institutional change after 1990
Allocative inefficiency parameters		
City	−1.9417 (0.3765)***	−1.9417 (0.3675)***
Airport authority	−2.2210 (0.4694)***	−2.5927 (0.5130)***
Port authority	−1.6517 (0.5579)***	−1.6517 (0.5446)***
City × Corruption	1.8699 (1.3102)	1.8699 (1.2789)
Airport authority × Corruption	1.9693 (1.4888)	2.7758 (1.6521)**
Port authority × Corruption	3.2210 (1.9254)**	3.2210 (1.8794)**
Technical inefficiency parameters (city-owned airports as the base)		
Airport authority	−1.5173 (0.4961)***	−1.7645 (0.4337)***
Port authority	0.0027 (0.4157)	1.1364 (0.8273)
City × Corruption	0.1785 (1.3187)	3.7059 (2.6569)
Airport authority × Corruption	5.7806 (2.0034)***	9.7049 (3.2168)***
Port authority × Corruption	0.4919 (1.7018)	0.6645 (1.6945)
Number of observations	55	50

[a] Numbers in parentheses are robust standard errors. Year fixed effects and control variables listed Table 3 are included in all estimations.
** Significant at 10% level.
*** Significant at 5% level.

Table A2
Additional robustness checks: estimation results from the variable factor productivity regressions (city-owned airports as the base).[a]

	(1) Full sample	(2) Drop airports with institutional change after 1990 and observations before 2003 or after 2008
Airport authority	1.3383 (0.1783) ***	1.7036 (0.2595) ***
Port authority	0.1479 (0.1077) ***	−0.0773 (0.1506)
City × Corruption	0.0045 (0.1417)	−0.0482 (0.1958)
Airport authority × Corruption	−4.4101 (0.5815) ***	−5.2614 (0.8090) ***
Port authority × Corruption	−1.2528 (0.4887) ***	−1.1610 (0.5994) **
Number of airports	55	50
Number of observations	495	300

[a] Numbers in parentheses are robust standard errors. Year fixed effects and control variables listed Table 3 are included in all estimations.
*** Significant at 5% level.
** Significant at 10% level.

(e_p^e) to maximize his expected payoff. Let the solution function be $e_p(e_p^e)$ and the solution function is a self-map on the effort space. The equilibrium effort level, which is denoted by e_p^*, is the fixed-point of the self-map and it satisfies the following first-order condition:

$$\frac{d}{de_p}\left(\int\left(\int \theta\frac{f(\theta,y_p|e_p^*)}{f(y_p|e_p^*)}d\theta\right)f(y_p|e_p)dy_p\right)\Bigg|_{e_p=e_p^*} = C_a^*(e_p^*) \tag{A1}$$

where $f(\theta, y_p|e_p)$ is the joint density of talent and productivity given a market's expectation on the manager's efforts and $f(y_p|e_p) = \int_\theta f(\theta,\ y_p|e_p)d\theta$. The first-order condition in (A1) implies

$$\mathrm{cov}\left(\theta,\frac{f_{e_p}(y_p|e_p)}{f(y_p|e_p)}\right) = C_a'(e^*) \tag{A2}$$

where $f_{e_p}(y_p|e_p)$ denotes the first-order derivative of the marginal density with respect to effort level. Given the independent normality assumptions on the distributions of θ and ε_p, we have

$$\mathrm{cov}\left(\theta,\frac{f_{e_p}(y_p|e_p)}{f(y_p|e_p)}\right) = \frac{1}{1+\sigma_\varepsilon^2/\sigma_\theta^2} \tag{A3}$$

Combining (A2) and (A3), we obtain the first order condition of the manager's equilibrium efforts on productive activities

$$C_a'(e_p^*) = \frac{1}{1+\sigma_\varepsilon^2/\sigma_\theta^2} \tag{A4}$$

When the manager spends efforts on the pet project ($e_p = 0$), he chooses efforts on the pet project and a positive deviation from the government's targeted variable input ratio to maximize his payoff. The optimal decisions can be characterized by the following first-order conditions

$$C_a'(e_g) = g(\tilde{m},\gamma) \text{ and } \frac{\partial g(\tilde{m},\gamma)}{\partial\tilde{m}} = 0 \tag{A5}$$

We use $e_g^*(\gamma)$ and $\tilde{m}^*(\gamma)$ to denote the solutions from the first-order conditions and they are functions of monitoring. The following proposition characterizes the manager's optimal decision rule responding to the board's monitoring.

Proposition 1.

1. Both $e_g^*(\gamma)$ and $\tilde{m}^*(\gamma)$ are strictly decreasing function of γ.
2. There exists uniquely a $\bar{\gamma}$. When $\gamma > \bar{\gamma}$, the manager does not pursue the pet project such that $e_g^* = 0$, $\tilde{m}^* = 0$ and e_p^* is determined by equation (4). When $\gamma < \bar{\gamma}$, the manager pursues the pet project such that $e_p^* = 0$, $e_g^* = e_g^*(\gamma)$ and $\tilde{m}^* = \tilde{m}^*(\gamma)$.

Proof. For point 1, differentiating the first-order conditions in (9) with respect to γ, we have

$$C_a''(e_g)\frac{de_g^*(\gamma)}{d\gamma} = \frac{\partial g(\tilde{m},\gamma)}{\partial\tilde{m}}\frac{d\tilde{m}^*(\gamma)}{d\gamma} + \frac{\partial g(\tilde{m},\gamma)}{\partial\gamma} \tag{A6}$$

$$\frac{\partial^2 g(\tilde{m},\gamma)}{\partial\tilde{m}^2}\frac{d\tilde{m}^*(\gamma)}{d\gamma} + \frac{\partial^2 g(\tilde{m},\gamma)}{\partial\tilde{m}\partial\gamma} = 0 \tag{A7}$$

From the assumptions $\frac{\partial g(\tilde{m},\gamma)}{\partial\tilde{m}} > 0$, $\frac{\partial^2 g(\tilde{m},\gamma)}{\partial\tilde{m}^2} < 0$, $\frac{\partial g(\tilde{m},\gamma)}{\partial\gamma} < 0$ and $\frac{\partial^2 g(\tilde{m},\gamma)}{\partial\tilde{m}\partial\gamma} < 0$, we can have both $\frac{de_g^*(\gamma)}{d\gamma} < 0$ and $\frac{d\tilde{m}^*(\gamma)}{d\gamma} < 0$.

For point 2, since we assume that $g(\tilde{m}^*(\gamma),\gamma) > \frac{1}{1+\sigma_\varepsilon^2/\sigma_\theta^2}$ for some γ, this conclusion can be obtained by showing that $g(\tilde{m}^*(\gamma),\gamma)$ is strictly decreasing in γ. From point 1, it is straightforward to show $\frac{dg(\tilde{m}^*(\gamma),\gamma)}{d\gamma} = \frac{\partial g(\tilde{m}^*(\gamma),\gamma)}{\partial \tilde{m}}\frac{d\tilde{m}^*(\gamma)}{d\gamma} + \frac{\partial g(\tilde{m}^*(\gamma),\gamma)}{\partial\gamma} < 0.$ □

Equilibrium monitoring efforts of the board are characterized as follows.

Proposition 2. Equilibrium monitoring effort level γ^* satisfies:

1. $\gamma^* \in [0,\bar{\gamma}]$.
2. γ^* is strictly increasing with respect to α in the open interval $(0,\bar{\gamma})$.
3. γ^* is less likely to be $\bar{\gamma}$ when α is less.

Proof. For (1), any a $\gamma^* > \bar{\gamma}$ cannot be hold because the board can always reduce monitoring efforts to boost the reward. For (2), when $\gamma^* \in (0,\bar{\gamma})$, it is the solution of $\text{argmax}_\gamma \alpha \cdot \lfloor \bar{\theta} - h(\tilde{m}^*(\gamma)) \rfloor - C_b(\gamma)$. The first order condition is $-\alpha \cdot h'(\tilde{m}^*)\frac{d\tilde{m}^*(\gamma)}{d\gamma}\Big|_{\gamma=\gamma^*} = C_b'(\gamma^*)$. Since the effort cost function is convex, γ^* decreases when α drops. For (3), let γ_L denote the optimal level of monitoring efforts in the interval $[0,\bar{\gamma})$, we have $\gamma^* = \bar{\gamma}$ if $\alpha \cdot \left[h(\tilde{m}^*(\gamma_L)) + c_a^{-1}\left(\frac{1}{1+\sigma_\varepsilon^2/\sigma_\theta^2}\right)\right] > C_b(\bar{\gamma}) - C_b(\gamma_L)$. $\Gamma(\alpha) \equiv \alpha \cdot \left[h(\tilde{m}^*(\gamma_L)) + c_a^{-1}\left(\frac{1}{1+\sigma_\varepsilon^2/\sigma_\theta^2}\right)\right]$ measures the utility gain to the board when the board switches monitoring level from γ_L to $\bar{\gamma}$ and the utility gain is strictly increasing with respect to α because $\Gamma'(\alpha) = h(\tilde{m}^*(\gamma_L)) + c_a^{-1}\left(\frac{1}{1+\sigma_\varepsilon^2/\sigma_\theta^2}\right) + \alpha h'(\cdot)\frac{d\tilde{m}^*(\gamma)}{\gamma}\Big|_{\gamma=\gamma_L}\frac{d\gamma_L}{d\alpha} > 0$. $C_b(\bar{\gamma}) - C_b(\gamma_L)$ increases when α decreases because γ_L is increasing with α. As such, the board is more likely to choose $\bar{\gamma}$ when α is larger. □

When the board chooses the high monitoring effort level, that is, $\gamma^* = \bar{\gamma}$, the manager of the airport authority is *ex ante* indifferent between pursuing and not pursuing the pet project. Therefore, he will not switch his efforts from productive activities to the pet project.

A.2. Technical derivation of result 2

This section derives formally result 2 in the text. If the multiple tasks are equally important to the voters such that the bureaucrat is evaluated based on the aggregate performance $Y_n \equiv \sum_{i=1}^n y_i$, the career concerns model for city-owned airports is a special case of the one in Dewatripont et al. (1999b), which shows that the positive equilibrium level of total efforts ($e^* \equiv \sum_{i=1}^n e_i^*$) is determined by

$$C'(e^*) = \frac{1}{n + \sigma_\varepsilon^2/\sigma_\theta^2} \tag{A8}$$

Under the assumption that the cost of efforts is a convex function, increasing the number of tasks decreases the positive equilibrium level of total efforts.

Under multiple tasks environment, the bureaucrat of a city-owned airport may focus on tasks which are more helpful in signaling his ability. Alesina and Tabellini (2008) show that such a misallocation of efforts can be caused by uncertain voters' preferences. For simplicity in illustration, we use y_o to denote the aggregate performance measure of other tasks excluding airport efficiency such that

$$y_o \equiv \sum_{i=1}^{n-1} y_i = \sum_{i=1}^{n-1} e_i + (n-1)\theta + \sum_{i=1}^{n-1}\varepsilon_i = e_o + (n-1)\theta + \varepsilon_o \tag{A9}$$

Let ω denote a Bernoulli random variable. In each period, the voters utility is given by $U(\omega y_o + (1-\omega)y_p)$ and $\Pr(\omega=1) > \frac{1}{2}$. Facing the uncertainty, the bureaucrat is assigned an unconditional measure of performance $x = \lambda y_0 + (1-\lambda)y_p$, where $\lambda \in [0,1]$. Given the assignment and the voters' expectation on effort levels (e_o^e, e_p^e), the bureaucrat solves

$$\max_{(e_o,e_p)} E\left(E(\theta\big|x, e_o^e, e_p^e)\right) - C(e_o + e_p) \tag{A10}$$

Because efforts are not separable, when $\Pr(\omega=1) > \frac{1}{2}$, it is optimal for the voters to set $\lambda = 1$. Let e_p^* and e_o^* denote equilibrium efforts, we have $e_p^* = 0$ and e_o^* is determined by the first-order condition $C'(e_o^*) = \frac{1}{n-1+\sigma_\varepsilon^2/\sigma_\theta^2}$. In this example, the bureaucrat focuses only on tasks that voters care about and therefore allocates zero effort on managing airport operation.

A.3. The empirical model under the translog parameterization

In estimation, the log variable cost frontier is approximated by the following *translog* functional form:

$$\begin{aligned}
\ln C_{it}^*(Q_{it}, W_{it}^*, K_{it}) \approx \ln \widetilde{C}_{it}(Q_{it}, W_{it}, K_{it}) &= \alpha + \vartheta D^T + \sum_{j=1}^{3}\beta_j \ln q_{jit} \\
&+ \sum_{j=1}^{2}\theta_j \ln k_{jit} + \sum_{j=1}^{2}\delta_j \ln \lambda_j w_{jit} \\
&+ \frac{1}{2}\sum_{j=1}^{3}\sum_{n=1}^{3}\phi_{jn}\ln q_{jit}\ln q_{nit} \\
&+ \sum_{j=1}^{3}\sum_{n=1}^{2}\gamma_{jn}\ln q_{jit}\ln \lambda_j w_{nit} \\
&+ \sum_{j=1}^{3}\sum_{n=1}^{2}\rho_{jn}\ln q_{jit}\ln k_{nit} \\
&+ \frac{1}{2}\sum_{j=1}^{2}\sum_{n=1}^{2}\tau_{jn}\ln \lambda_j w_{jit}\ln \lambda_n w_{nit} \\
&+ \sum_{j=1}^{2}\sum_{n=1}^{2}\zeta_{jn}\ln k_{jit}\ln \lambda_n w_{nit} \\
&+ \frac{1}{2}\sum_{j=1}^{2}\sum_{n=1}^{2}\psi_{jn}\ln k_{jit}\ln k_{nit}
\end{aligned} \tag{A11}$$

where D^T represents a vector of year dummies which capture technical change. The shadow share of labor inputs is expressed as

$$\begin{aligned}
S_{1it}^* &\equiv \frac{\partial \ln C_{it}^*(Q_{it}, W_{it}^*, K_{it})}{\partial \ln w_{1it}^*} \approx \frac{\partial \ln \widetilde{C}_{it}(Q_{it}, W_{it}^*, K_{it})}{\partial \ln w_{1it}^*} \\
&= \delta_1 + \sum_{j=1}^{3}\gamma_{j1}\ln q_{jit} + \sum_{j=1}^{2}\tau_{j1}\ln w_{jit}^* + \sum_{j=1}^{2}\zeta_{j1}\ln k_{jit}
\end{aligned} \tag{A12}$$

Substituting (A11) and (A12) into Eqs. (6) and (7) of the text, we obtain the estimable variable cost frontier model which incorporates both technical and allocative efficiency.

As the usual practice to estimate the translog cost system, we impose the following constraints in estimation. 1. Symmetric constraints: $\phi_{12} = \phi_{21}$, $\phi_{13} = \phi_{31}$, $\phi_{23} = \phi_{32}$, $\tau_{12} = \tau_{21}$, $\psi_{12} = \psi_{21}$. 2. Homogeneity constraints: The variable cost frontier is homogeneous of degree 1 with respect to variable input prices, so we have $\delta_1 + \delta_2 = 1$, $\gamma_{11} + \gamma_{12} = 0$, $\gamma_{21} + \gamma_{22} = 0$, $\gamma_{31} + \gamma_{32} = 0$, $\tau_{11} + \tau_{12} = 0$, $\tau_{12} + \tau_{22} = 0$, $\zeta_{11} + \zeta_{12} = 0$, $\zeta_{21} + \zeta_{22} = 0$. A well-defined variable cost frontier should also be concave with respect to variable input prices, which requires that the Hessian matrix of the variable cost frontier with respect to input prices is negative semidefinite. As shown by Diewert and Wales (1987), the Hessian matrix is negative semidefinite if and only if $\tau \equiv \begin{pmatrix} \tau_{11} & \tau_{12} \\ \tau_{12} & \tau_{22} \end{pmatrix}$ is negative semidefinite. Combining this with homogeneity constraints, the concavity condition can be imposed by restricting $\tau_{11} \leqslant 0$.

A.4. The GMM estimation

Let $e_i = (\varepsilon^c_{i1}, \varepsilon^c_{i2}, \ldots, \varepsilon^c_{iT}, \varepsilon^s_{i1}, \varepsilon^s_{i2}, \ldots, \varepsilon^s_{iT})' = \begin{pmatrix} \varepsilon^c_i \\ \varepsilon^s_i \end{pmatrix}_{2T\times 1}$ and $V_i = \begin{pmatrix} V_{i1} \\ V_{i2} \\ \vdots \\ V_{iT} \end{pmatrix}$, where T is the number of years and W_{it} is the vector of regressors in Eq. (5). The orthogonal conditions in Eq. (12) of the text implies

$$\mathbf{E}\left(\begin{bmatrix} V_i' & \mathbf{0} \\ \mathbf{0} & V_i' \end{bmatrix} \times e_i \right) = \mathbf{E}(H_i \times e_i) = \mathbf{0}_{2k\times 1} \tag{A13}$$

The empirical analog to the moment conditions in (A13) is

$$J(\Theta) = (N)^{-1} \sum_{i=1}^{N} H_i \times e_i \tag{A14}$$

where N is the number of airports; Θ is the vector of unknown parameters in Eqs. (5) and (6) of the text. For some weighting matrix $\Phi_{2k\times 2k}$, the GMM estimator of Θ is the solution to the following minimization problem:

$$\widehat{\Theta} = \arg\min_{\theta} J(\Theta)' \times \Phi \times J(\Theta) \tag{A15}$$

The optimal weighting matrix is the inverse of the variance–covariance matrix of the moment functions and takes the following form:

$$\Phi^* = \left((N)^{-1} \sum_{i=1}^{N} H_i \mathrm{var}(e_i) H_i' \right)^{-1} \tag{A16}$$

where $\mathrm{var}(e_i)$ is specified in Eq. (9) of the text. We first solve the optimization problem in (A15) to obtain consistent parameter estimates by specifying $\mathrm{var}(e_i)$ as the identity matrix. Given consistent parameter estimates, we use the residuals $\hat{e}_i = (\hat{\varepsilon}^c_{i1}, \hat{\varepsilon}^c_{i2}, \ldots, \hat{\varepsilon}^c_{iT}, \hat{\varepsilon}^s_{i1}, \hat{\varepsilon}^s_{i2}, \ldots, \hat{\varepsilon}^s_{iT})'$ to estimate $\mathrm{var}(e_i)$, thereby obtaining more efficient parameter estimates because we use the estimated optimal weighting matrix to resolve the optimization problem in (A15). Specifically, the empirical variance of $\left(\hat{\varepsilon}^c_{it} - \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}^c_{it} \right)$ gives us a consistent estimate of $\mathrm{var}(\xi^c_{it})$; the empirical variance of $\hat{\varepsilon}^c_{it}$ gives us a consistent estimate of $\mathrm{var}(\mu_i) + \mathrm{var}(\omega_i) + \mathrm{var}(\xi^c_{it})$;, the empirical variance of $\left(\hat{\varepsilon}^s_{it} - \frac{1}{T}\sum_{t=1}^{T} \hat{\varepsilon}^s_{it} \right)$ gives us a consistent estimate of $\mathrm{var}(\xi^s_{it})$; the empirical variance of $\hat{\varepsilon}^s_{it}$ gives us a consistent estimate of $\mathrm{var}(\omega_i) + \mathrm{var}(\xi^c_{it})$; combining the four consistent estimates, we obtain a consistent estimate of $\mathrm{var}(e_i)$. The variance–covariance matrix of the GMM estimates is $(G\Phi^* G')^{-1}$, where G is the gradient vector of $J(\Theta)$ evaluated at the GMM estimates.

A.5. Robustness checks

In this section, we present estimations results from the two robustness checks described in Section 4.1 of the text (Tables A1 and A2).

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