

The Social Cost of Fiscal Federalism and the Depletion of China's Native Forests

Haoyu Wang

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Gregory S. Amacher, Chair

Jintao Xu

Kelly Michele Cobourn

Stella Zucchetti Schons Do Valle

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(ABSTRACT)

China's key forested region is located in the northeast. This region consists of state forest enterprises which manage harvesting and reforestation and have represented the most important source of wood supplies since the 1950s. Deforestation is a major problem there, however, and has resulted in several central government reforms. We develop a framework for assessing the social cost of state forest enterprise deforestation. We first develop a two-principal, one-agent model that fits the federalistic organization state forests, in that state forest managers make (potentially hidden) decisions under influence of provincial and central government policies and quotas meant to direct manager behavior. This model is used to derive an expression of the social cost of these hidden actions as well as a comparison of first and second best government policies. We then use panel data from a survey conducted by the Environmental Economics Program in China (EEPC) to compute social welfare losses and use a regression approach to confirm the main factors in these costs in practice. A sensitivity analysis shows that lower harvesting limits and a more accurate monitoring system are the keys to lowering social welfare loss. These are more important than conventional instruments used by the governments such as wages for managers that achieve certain targets. Through regression analysis we find that the remote areas with a higher percentage of mature natural forests are the ones that will always have the highest social welfare loss. These areas are the hardest to monitor, but our results show they must be a critical focus moving forward.

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(GENERAL AUDIENCE ABSTRACT)

China's key forested region is located in the northeast. This region consists of state forest enterprises which manage harvesting and reforestation and have represented the most important source of wood supplies since the 1950s. Deforestation is a major problem there. We develop a framework for assessing the damage to the society because of deforestation. We develop a theoretical model to describe the forest management structure, in which state forest managers make (potentially hidden) decisions under influence of provincial and central government policies. This model is used to derive an expression of the damage. We then use data from a survey conducted by the Environmental Economics Program in China (EEPC) to compute the damage and confirm the main factors in these damages in practice. We find that lower harvesting limits and a more accurate monitoring system are the keys to lowering the damage. These are more important than conventional instruments used by the governments such as wages for managers that achieve certain targets. We also find that the remote areas with a higher percentage of mature natural forests are the ones that will always have the largest damage. These areas are the hardest to monitor, but our results show they must be a critical focus moving forward.

Dedication

To my father and mother

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List of Abbreviations

NFPP National Forest Protection Program

SFE State Forest Enterprise

SFE is state-owned enterprise managing the national forest in Northeast China.

NFPP is National Forest Protection Program. It was formally implemented in 2000 to address this deforestation. The first phase of NFPP is from 2000 to 2010 and the second phase is from 2011 to 2020.

Chapter 1

Introduction

China's key forested region is located in the northeast and encompasses the Heilongjiang, Jilin, and Inner Mongolia provinces. This region has been the most important source of wood supplies since the 1950s and remains the most important wood basket of the country, producing over 20 million cubic meters of lumber per year, accounting for more than one half of the national total (Xu, 2013). It has also been an area of historic and unprecedented degradation, where harvesting and high grading of forest stocks and lack of reforestation has been the rule for decades (Jiang et al. 2014).

Forest harvesting decisions within the Northeast Region are the responsibility of managers for state forest enterprises (SFEs). These are de facto government-owned entities and are managed by a director who receives wages and continued appointments from both local (provincial) and central governments based on harvest income generation. However, the director is, in theory, required to generate this income while staying within central government quotas on harvesting and reforestation. Meeting these quotas implies reduced tax revenue to local governments, less income to the SFE manager, and less regional economic growth.

Central government quotas were instituted during the market reforms of the 1980s to prevent further degradation of Chinese state forests. Despite their promise, deforestation has remained a constant concern, and state forest enterprises have been blamed for encouraging illegal logging and not meeting required reforestation targets for decades (Xu et al. 2004). One

often cited reason for this is that, in the mid-1980s, SFEs faced resource and financial crises, and by the 2000s, ninety percent of state forests had almost depleted their mature forests (Xu, 2013). The National Forest Protection Program (NFPP) was formally implemented in 2000 to address this deforestation; the NFPP required cessation of commercial harvesting on 670 million hectares of state-owned forest and increased SFE manager average annual incomes over 300% or 6,400 USD.¹ The purpose was to reduce incentives for these managers to generate income through illegal harvesting.

Despite these new reforms, strong incentives remained for SFE managers to deviate from central government quotas. These continue to represent a lingering feature of a now decentralized market economy but a continued centralized political system. The most important reason for the disincentive is that the salaries of SFE managers still depend in part on provincial governments. Provincial governments value harvesting for local economic growth, and as a result it is very likely that central and local governments do not have perfect incentives to cooperate. Local governments impacted by SFEs have incentives to pressure directors to increase harvesting and contribute to local economic growth and tax revenues. The central government, however, principally has sought to promote lower harvest quotas with at least some objective of conservation in mind. This incentive incompatible problem has been discussed many times in the literature and blamed for significant continued forest loss and lack of reforestation (Xu, Tao and Amacher 2004, Yi, Habla and Xu 2017).

The incentive problems inherent in Chinese state forestry represent both an unusual type of mechanism design problem and a more classical problem of fiscal federalism in economics. Federalism is a consequence of the fact that central and local governments serve different constituents and face different revenue constraints. Additionally, the incentive problems do not fit into a standard hidden actions problem in mechanism design, which assumes a single

¹The first phase of NFPP is from 2000 to 2010 and the second phase is from 2011 to 2020.

principal attempting to control the performance of an agent using various instruments. The Chinese forestry problem is much more complex. Not only do SFE managers answer to the central government, but they also generate revenues for their local government. Both central and local governments impact the income of SFE managers through continued appointments and harvest revenue sharing. This type of problem is a two-principal, one-agent mechanism where actions of the SFE are hidden from one of the principals (central government). Thus, while the classic mechanism design problem leads to straightforward rules about using policy instruments to achieve first best outcomes, the impact of policies by any one government in the Chinese forestry case may not lead to a first best result.

In this paper, we determine the increase in social costs, and the factors affecting this increase, when a second best (federalistic) outcome arises in Chinese state forest management compared to a theoretical first best (perfect coordination) outcome. We use a two principal/single agent approach that reveals incentive problems inherent in the failures of local and central governments to coordinate with respect to SFE management. The consequences of these failures to deforestation and the choice of policies are also examined. Although our basic approach is static, we incorporate aspects of the dynamic problem where important, such as SFE manager income streams; our problem is also consistent with the observation that many policies, such as quotas or local taxes, are set and forget investments by governments. This allows focus on the incentive problems that the Chinese SFE system creates, as these would be present in similar fashions in more dynamic treatments of the problem. The importance of allowing for two governments who control policies and impact SFE managers differently is more important than the growth of the forest over time to the results. Moreover, the incentives we model would also not change in a more dynamic problem.

The problem of SFEs and deforestation has already been argued to be a case of Chinese-style fiscal federalism (Montinola et al., 1995; Qian and Weingast, 1997; Xu, 2011), but this work

does not consider incentive problems among SFE managers. It has also been argued that hidden actions of SFE managers will always be present given that monitoring costs of the scale required of state forests is prohibitively high, making it impossible for the central government to receive a perfect signal of SFE practices (Xu, Tao and Amacher 2004). There is only one closely related article to our study that considers incentives of SFE managers in a two-principal, one-agent model (Yi et al. 2017). Yi et al. find that deforestation is more likely to happen in larger forest areas, as the monitoring cost is higher or profit sharing is higher. Their model focuses mainly on the decision making of the SFE manager. We add utility functions for the provincial government and the central government to analyze their decision making as well, and most importantly we develop an expression that represents the social costs of these interactions. We also investigate factors that influence these costs using data from SFEs in the Northeastern region. Our analysis will therefore inform future discussions concerning the best instruments to achieve deforestation limits in China that are incentive compatible.

Our work also contributes more broadly in three ways. First, environmental studies in China have found that pollution emissions are positively correlated with fiscal decentralization (Zhang, Wang and Cui 2011). Hong, Yu and Mao (2019) found that local government officials in China have a powerful motivation to ease environmental regulations for economic growth. Our paper shows the same motivation of prioritizing economic growth over forest protection in northeast state forests, but we also quantify this by computing social costs associated with poorly used policies. Second, this paper contributes to the general regulatory federalism literature, which has established that inefficiencies of imperfect coordination vanish when governments share revenues. In the forestry problem, the inefficiency occurs not only from coordination failures but also from hidden actions inherent in forest harvest monitoring, and

the fact that forest stock can be thought of as a public good.² In the environmental literature, uniform standards are proposed to reduce interjurisdictional competition. However, regulation of SFEs are already based on a uniform standard system set by China's State Forest Agency (SFA). The SFA has incomplete information on actual harvesting due to a high monitoring cost. As we will show, decentralization of the right to set harvest standards may actually be a solution for this incomplete information problem given that SFEs are fixed and cannot "move" across provinces.

The paper is structured as follows: Section 2 sets the theoretical framework of the model and introduces the idea of social cost in this context. In Section 3, we describe our data, calculate the social cost; and perform a sensitivity analysis of our results. A regression analyses of social cost factors is presented in Section 4. Our concluding comments are given in Section 5.

²Amacher (2002) previously showed that revenue sharing can actually create incentives of increasing public harvesting in a simple federalism model of U.S. national forest management.

Chapter 2

Theoretical Model

In this section we model differences in incentives of the SFE managers and the principals (local and central governments). We also develop a social cost function that depends on various policy and natural resource factors. Later we calculate social costs and study their determinants using data on multiple SFEs in Northeast China SFEs between 1980-2008.¹

2.1 Two principal, one agent model

Figure 2.1 describes the organization of Chinese government forest management and the way in which transfers and harvesting decisions are made by the SFE manager and the provincial and central governments in practice. The agent is the SFE manager, serving two principals: the central government and the provincial government. The central government sets harvest limits (quotas) (\bar{x}) to prevent negative forest growth rates (see Xu et al., 2002 for a discussion of this policy in practice).²

The central government must employ costly monitoring of the SFE. If an SFE is found

¹There are some examples that have considered multiple principals and agents in different contexts. Groenendijk (1997) used a two principal one agent model to describe corruption. In their model, one principal is corrupted and the other is not. A multi principal, one agent model is used in Delacote et al.,(2014), who showed that the existence of multiple principals reduces information rents in a spatial game. Larsen (2007) used a two principal and one agent model for European Union trade negotiations involving South Africa for a different purpose than our work.

²There are documented examples where SFE managers have harvested significantly over these limits, however (e.g., Economy, 1997; Alford and Shen, 1998; Brandt and Zhu, 2000).

to be harvesting more than the limit, then a fine of f is imposed. The local government makes a promotion decision concerning the SFE manager. If promoted, the present value sum of all the future salary increases is assumed to equal b . To increase the chance of promotion, the SFE manager retains enough profit from harvesting to cover the welfare (wages plus benefits) expenditure (G) for SFE employees and transfers the remainder ($\gamma\pi$) to the provincial government. This creates incentives of over harvesting in that the SFE managers will likely pursue short-term profits.

The fact that provincial governments benefit from exploiting resources has support in related environmental literature for China. For example, Zhang, Wang and Cui (2011) found that pollution emissions for local firms are positively correlated with fiscal decentralization, while Li and Chan (2016) found that small and medium state-owned enterprises spend less on pollution abatement. These studies support the fact that provincial governments are likely to act on their own and cooperate with state-owned enterprises to generate higher profits.

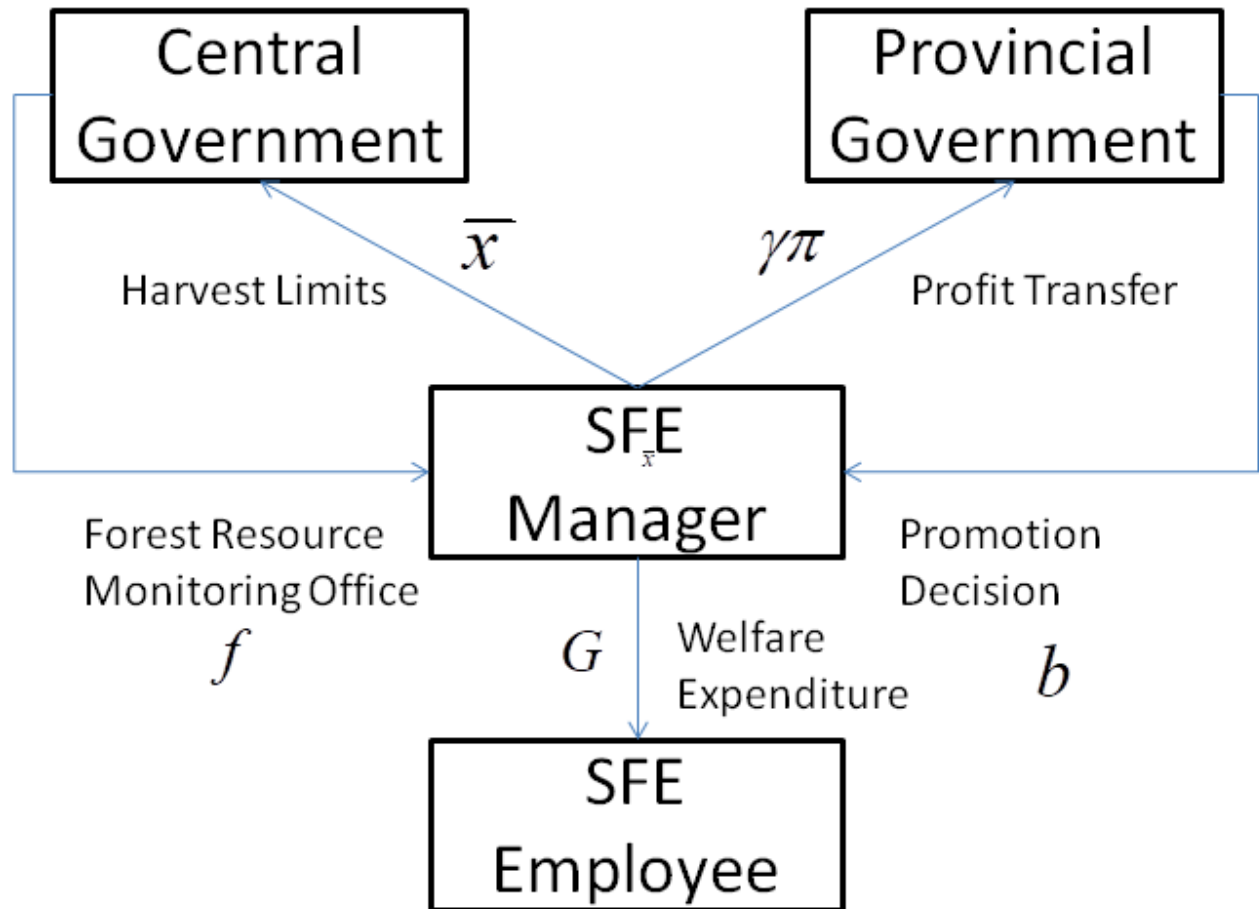


Figure 2.1: Two principal, one agent model of Chinese State Forest Enterprises

2.2 Solution of the two principal, one agent model

Yi et al. (2017) considered only the utility function of the SFE manager. We adjust the utility function to a quasilinear form and add the utility functions for the provincial and central governments. The quasilinear specification makes sense because the financial part comes in a linear way, while the impact of harvesting and the harvest limit come in nonlinearly. This is consistent with lots of utility functions in forest resources (Koskela and Ollikainen 1997, Amacher et al. 2002, Ovaskainen et al. 2006) including the Hartman problem used in rotation analysis (Hartman 1976).

2.2.1 Agent: SFE

We model wages in present value terms following Boskin (1974) and Menchik et al. (1983). Thus, \bar{w} is the present value sum of all future wages for the SFE manager. The term b is the present value sum of all future wage increases if the manager is promoted. This term captures the present value of the net benefits of promotion. We assume that the manager is promoted with probability $(1 - \frac{1}{\gamma\pi})$. This probability increases in the rate of profit shared with the provincial government (γ) and the profit of the enterprise (π). The larger the profit transfer $\gamma\pi$ is, the more likely the manager will be promoted.

SFE profit depends on forest harvesting revenue and costs:

$$\pi = (1 - \tau)(Px - C(x)), \quad (2.1)$$

where x is the harvest amount chosen by the SFE manager, P is an exogenous price, $C(x)$ is the cost of harvesting³, and τ is a tax levied by the provincial government on harvesting

³In our data, the cost function could in principle be different across SFEs.

profit. In addition to harvest level, the SFE manager chooses γ , which defines the transfer of net profit π to the provincial government. A higher γ increases the chance of promotion. The present value of the fine imposed by the central government if they catch the manager harvesting over the limit \bar{x} is $f \in (0, +\infty)$. Due to the high cost of perfect monitoring, the central government observes an imperfect signal of this harvest level given by:

$$x^s = \mu(x) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, \sigma^2). \quad (2.2)$$

The cost function for monitoring is $m(\sigma)$ with $m'(\sigma) < 0$, thus, in order to receive a more accurate signal, the monitoring cost paid must be higher. The probability of the enterprise being fined is then defined by: $(1 - e^{\bar{x} - x^s})$. Thus, and reasonably, the larger the gap of the harvest level and the quota, the more likely an SFE will be caught and fined. This fits with previous literature suggesting that larger SFEs with higher harvesting levels are more likely to overharvest.

With the building blocks above, the SFE is represented by the manager who has an expected utility function given by:

$$\text{EU} = \text{E} \left[\bar{w} + b \left(1 - \frac{1}{\gamma\pi} \right) - f (1 - e^{\bar{x} - x^s}) \right]. \quad (2.3)$$

In what follows we will use the rule $\text{E} [e^{k\epsilon}] = e^{\frac{k^2\sigma^2}{2}}$, and therefore rewrite equation (2.3) as:

$$\text{EU} = \bar{w} + b \left(1 - \frac{1}{\gamma\pi} \right) - f \left(1 - e^{\bar{x} - \mu(x) - \frac{\sigma^2}{2}} \right). \quad (2.4)$$

The agent (SFE manager) maximizes their expected utility function by choosing γ and x .

The first order conditions for this problem are:

$$\frac{b}{\gamma^2 \pi} > 0; \quad (2.5)$$

$$\frac{b}{\gamma \pi^2} (1 - \tau) [P - C'(x)] - f \mu'(x) e^{\bar{x} - \mu(x) - \frac{\sigma^2}{2}} = 0. \quad (2.6)$$

First, notice that equation (2.5) cannot be binding. Therefore the manager will choose the transfer γ to be as large as possible. Intuitively, the manager would like to transfer as much profit as possible to the provincial government in order to guarantee the highest possible chance of promotion.

The constraint on γ is $(1 - \gamma)\pi - G \geq 0$, where G is the welfare expenditure for the employees in the enterprise. The manager chooses a transfer rate that makes the enterprise's income cover its expenditure (in welfare terms).⁴ That is,

$$\gamma = 1 - \frac{G}{(1 - \tau)(Px - C(x))}. \quad (2.7)$$

In equation (2.6), the SFE manager equates the marginal benefit of an additional unit of harvesting (first term) to the marginal cost of harvesting one more unit (second term). From equation (2.6) and (2.7), the manager then solves for the optimal level of harvesting x^0 and transfer γ^0 .

Assuming as is convention that this maximization problem is concave, that is $\beta = \frac{\partial^2 EU}{\partial x^2} < 0$,

⁴By law in China, SFEs provide social services for their localities (e.g., see Groves et al., 1995). This includes wages, housing, education, health care and pension benefits.

we have the following comparative static results:

$$\frac{\partial x}{\partial b} = \frac{-(1 - \tau)(P - C'(x))}{\gamma\pi^2\beta} > 0; \quad (2.8)$$

$$\frac{\partial x}{\partial f} = \frac{\mu'(x)e^{\bar{x} - \mu(x) - \frac{\sigma^2}{2}}}{\beta} < 0; \quad (2.9)$$

$$\frac{\partial x}{\partial \bar{x}} = \frac{f\mu'(x)e^{\bar{x} - \mu(x) - \frac{\sigma^2}{2}}}{\beta} > 0; \quad (2.10)$$

$$\frac{\partial x}{\partial \sigma} = \frac{-f\sigma\mu'(x)e^{\bar{x} - \mu(x) - \frac{\sigma^2}{2}}}{\beta} > 0. \quad (2.11)$$

These results make sense. A higher promotion net benefit b increases the SFE manager's incentive to choose greater harvesting. A higher fine for exceeding the harvesting limit, if caught, leads to less harvesting. A more lenient harvest limit obviously leads to increased harvesting because costly monitoring by the central government is less effective. Similarly, if the central government receives a less accurate signal (i.e., one with a higher variance), then there are also incentives for the SFE manager to increase harvesting and deforestation.

These results show the power of the disincentives involved in this problem, but also the critical parameters that the central government must consider in trying to achieve a better outcome that reduces social costs. Any parameter change that increases harvesting will, as we will show later, increase social costs through greater deforestation than is optimal relative to achieving the first best outcome.

2.2.2 Principal 1: the Provincial Government

Using backward induction, the provincial government knows x^0 and γ^0 , and uses these to solve for their best response, determining the net promotion benefit for the SFE manager, b . This can also be interpreted without loss as continued appointment of the manager. The

provincial government's utility function is;

$$U_p = \gamma\pi + \tau(Px - C(x)). \quad (2.12)$$

Equation (2.12) includes two parts: $\tau(Px - C(x))$ is the tax paid by the SFE and $\gamma\pi$ is the profit transfer. The provincial government solves for the optimal b according to the following first order condition:

$$\frac{\partial U_p}{\partial b} = \frac{\partial \gamma^0}{\partial b} \pi^0 + \tau(1 - \gamma^0) \left(P \frac{\partial x^0}{\partial b} - C'(x^0) \frac{\partial x^0}{\partial b} \right) > 0. \quad (2.13)$$

(where $\pi^0 = (1 - \tau)(Px^0 - C(x^0))$)

Equation (2.13) suggests that the provincial government wants to set b as large as possible, and thus so $b = \bar{b}$ (\bar{b} is the upper bound for b).

2.2.3 Principal 2: the Central Government

The central government's utility function is:

$$U_c = f(1 - e^{\bar{x} - \mu(x) - \frac{\sigma^2}{2}}) + S - \mu(x) - m(\sigma). \quad (2.14)$$

Equation (2.14) includes three parts: the fine income $f(1 - e^{\bar{x} - \mu(x) - \frac{\sigma^2}{2}})$, the forest stock benefit, and the monitoring cost $m(\sigma)$. The term $f(1 - e^{\bar{x} - \mu(x) - \frac{\sigma^2}{2}})$ is the expected income from using the fine.

The term $S - \mu(x)$ is the central government's utility function as a function of the forest stock, where S is forest stock and $\mu(x)$ is the observation of SFE harvesting by the central government. They must use $\mu(x)$ in their utility function as they have incomplete information

about actual harvesting. The term $m(\sigma)$ is the monitoring cost, where $m'(\sigma) < 0$; thus, a more accurate signal costs more for the central government to acquire.

The central government has the following choices here: the fine f , the harvesting limit \bar{x} , and indirectly the monitoring accuracy σ . The central government chooses f , \bar{x} and σ according to the following first order conditions:

$$1 - e^{\bar{x} - \mu(x^0) - \frac{\sigma^2}{2}} - \mu'(x^0) \frac{\partial x^0}{\partial f} = -f e^{\bar{x} - \mu(x^0) - \frac{\sigma^2}{2}} \mu'(x^0) \frac{\partial x^0}{\partial f}; \quad (2.15)$$

$$f e^{\bar{x} - \mu(x^0) - \frac{\sigma^2}{2}} \mu'(x^0) \frac{\partial x^0}{\partial \bar{x}} - f e^{\bar{x} - \mu(x^0) - \frac{\sigma^2}{2}} - \mu'(x^0) \frac{\partial x^0}{\partial \bar{x}} = 0; \quad (2.16)$$

$$f e^{\bar{x} - \mu(x^0) - \frac{\sigma^2}{2}} (\mu'(x^0) \frac{\partial x^0}{\partial \sigma} + \sigma) - m'(\sigma) = \mu'(x^0) \frac{\partial x^0}{\partial \sigma}. \quad (2.17)$$

In equation (2.15), the left hand side is the marginal benefit of a higher fine. This includes a higher direct fine income and the utility of forest stock by a more severe punishment. The right hand side is the marginal cost of a higher fine; a higher fine decreases SFE harvesting levels as we showed earlier, thus the possibility of catching a SFE violating the limits is lower.

In equation (2.16), the first term is the marginal benefit of a higher harvesting limit: a higher limit means more harvesting and an increased likelihood of catching the SFE in violation and collecting the fine. The second term is the marginal cost of a higher limit. A higher limit also means more harvesting and less forest stock. This is represented as a cost to the government in the third term.

In equation (2.17), the left hand side is the marginal benefit of a larger signal variability. Larger variation means the monitoring result can be higher or lower. If the result is higher, the chance of catching the cheating SFE and the resulting fine payment are greater. This is the benefit to the central government in the first term. An inaccurate signal (higher

variability) also costs less, and this is represented as a benefit in the second term. The right hand side is the marginal cost of a larger signal variation, as a lower monitoring result provides an incentive for the SFE to increase harvesting and lower the forest stock, all of which represent a social welfare loss to the central government.

2.3 Social welfare losses in the second best outcome

If central and provincial governments and the SFE manager do not perfectly coordinate, which we have shown would not happen in general, then the situation is the two principal, one agent model we solved above. This represents the best second-best outcome achievable in the Chinese forestry problem. We now define the corresponding second best social welfare function and eventually compare it with the theoretical first best social welfare. This comparison allows us to derive an expression for the social cost of federalism and hidden actions with respect to SFE harvesting. Later in the empirical-based simulation we compute this using data for a range of small and large SFEs in northeastern China.

The social welfare function consists of the utility of the SFE manager, the provincial government's utility, the central government's utility, and finally the utility of the SFE employees.⁵

$$SW(S^0) = \bar{w} + \bar{b}\left(1 - \frac{1}{\gamma^0(1-\tau)(Px^0 - C(x^0))}\right) + Px^0 - C(x^0) + S - \mu(x^0) - m(\sigma_0), \quad (2.18)$$

where γ^0 and x^0 are the solutions of equation (2.6) and (2.7), and σ_0 is the solution of equation (2.15) to (2.17). The term $\bar{w} + \bar{b}\left(1 - \frac{1}{\gamma^0(1-\tau)(Px^0 - C(x^0))}\right)$ is the wage income of the SFE manager, and $Px^0 - C(x^0)$ is the SFE profit. The term $S - \mu(x^0)$ is the forest stock

⁵We consider the fourth part as SFE employees; they enjoy the SFE profit that is not transferred to the provincial government, $(1 - \gamma^0)(1 - \tau)(Px^0 - C(x^0))$, as their welfare expenditure.

benefit, and $m(\sigma_0)$ is the total monitoring cost.

2.4 First best social welfare

Now we can discuss the first best outcome and the resulting social welfare. This is a situation where the central government has perfect information about actual harvesting on the SFE, and all levels of governments perfectly cooperate to maximize the social welfare. The two principal governments can therefore structure instruments to achieve the first best outcome. The social welfare function in this case is:

$$SW = \bar{w} + b\left(1 - \frac{1}{\gamma(1-\tau)(Px - C(x))}\right) + Px - C(x) + S - x, \quad (2.19)$$

Notice that we now have x instead of $\mu(x)$ and we drop the monitoring cost $m(\sigma)$ because there is perfect information. Social welfare consists of the SFE manager wage income ($\bar{w} + b(1 - \frac{1}{\gamma(1-\tau)(Px - C(x))})$), SFE revenue $Px - C(x)$, and the public forest stock benefit $S - x$. More harvesting increases the SFE manager wage income and SFE revenue. However, it decreases the forest stock benefit. We solve for the optimal level of harvesting.

The central government maximizes SW by choosing b , γ and x . The necessary conditions suggest that the first best solution requires γ and b to be as large as possible:

$$\gamma = 1 - \frac{G}{(1-\tau)(Px - C(x))}; \quad (2.20)$$

$$b = \bar{b}. \quad (2.21)$$

The first order condition for x is:

$$\frac{b}{\gamma(1-\tau)(Px - C(x))^2}(P - C'(x)) + P - C'(x) = 1. \quad (2.22)$$

In equation (2.22), the left hand side is the marginal benefit of additional harvesting. This induces a greater promotion chance for the SFE manager (the first term) and higher profit for the SFE (the second term). The right hand side is the marginal social cost of additional harvesting as a function of the forest stock decrease.

Solving equation (2.20) and (2.22), we have a solution for the pair x^* and γ^* . We can now define first best social welfare using the first best solution pair as:

$$SW(S^*) = \bar{w} + \bar{b}\left(1 - \frac{1}{\gamma^*(1-\tau)(Px^* - C(x^*))}\right) + Px^* - C(x^*) + S - x^*. \quad (2.23)$$

Comparing this to the second best social welfare function derived above, we have a term that represents the social welfare loss (i.e., social cost) of federalism and hidden actions for the Chinese state forestry problem. This social welfare loss is therefore defined formally as:

$$\begin{aligned} SWL = SW(S^*) - SW(S^0) = & \bar{b}\left(\frac{1}{\gamma^0(1-\tau)(Px^0 - C(x^0))} - \frac{1}{\gamma^*(1-\tau)(Px^* - C(x^*))}\right) \\ & + Px^* - C(x^*) - (Px^0 - C(x^0)) + \mu(x^0) - x^* + m(\sigma_0), \end{aligned} \quad (2.24)$$

where γ^0 , x^0 , γ^* , x^* and σ_0 are solved from the corresponding equations. Social welfare losses therefore consist of the lost forest stock benefit due to over-harvesting $\mu(x^0) - x^*$ and the saved monitoring cost $m(\sigma_0)$. However, this is offset by the higher profits $Px^* - C(x^*) - (Px^0 - C(x^0))$, and the greater promotion chance for the SFE manager $\bar{b}\left(\frac{1}{\gamma^0(1-\tau)(Px^0 - C(x^0))} - \frac{1}{\gamma^*(1-\tau)(Px^* - C(x^*))}\right)$ in an over-harvesting situation.

There is one additional case to consider. There are some arguments in the regulatory literature that fines or emissions tax revenues should not be part of any government's welfare function (Hettich 1998, Bento and Parry 1999, Murray and Nicholas 2015).

Suppose the central government does not include SFE fine income in their utility function. The interpretation is that the central government is purely concerned with the utility of forest conservation (a public good). Again, as above, we define the second best outcome under hidden actions and federalism, and the first best perfect coordination outcome with no cheating on the part of the SFE. The social welfare loss function can then be derived from the difference of these functions.

The second best decisions for the SFE and provincial government stay the same and do not depend on removal of fine revenue from social costs. The central government's problem is different, however. The central government's utility for the second best case becomes:

$$U_c = S - \mu(x^0) - m(\sigma). \quad (2.25)$$

The first order condition for \bar{x} is:

$$-\mu'(x^0) \frac{\partial x^0}{\bar{x}} = 0. \quad (2.26)$$

This is not possible as $\frac{\partial x^0}{\bar{x}} > 0$, and $\mu'(x^0) > 0$. The central government wants the target \bar{x} to be as small as possible, as a smaller target means less harvesting. However, there should be a lower bound for \bar{x} , denoted as \bar{x}^0 .

The first order condition for σ is:

$$-\mu'(x^0) \frac{\partial x^0}{\partial \sigma} - m'(\sigma) > 0. \quad (2.27)$$

This suggests σ should be as large as possible. As the central government does not care about the fine revenue in this case, it seeks only to minimize the cost of monitoring. Therefore, the central government will not do any monitoring, and as a result $\sigma = \sigma_0$, where σ_0 is the largest value for σ .

The second best social welfare function is:

$$SW(S^0) = \bar{w} + \bar{b}\left(1 - \frac{1}{\gamma^0(1-\tau)(Px^0 - C(x^0))}\right) - f\left(1 - e^{\bar{x}^0 - \mu(x^0) - \frac{\sigma_0^2}{2}}\right) + Px^0 - C(x^0) + S - \mu(x^0) - m(\sigma_0). \quad (2.28)$$

Because the central government does not care about fine revenue, we can without loss think of the fine as simply a fixed value set by the central government, so that f is some constant in our model. The term $-f\left(1 - e^{\bar{x}^0 - \mu(x^0) - \frac{\sigma_0^2}{2}}\right)$ in equation (2.28) then defines lost utility of SFE due to the fine by the central government. We do not see this term in the second best social welfare equation when the central government considers the fine revenue in equation (2.18). Because the fine is a loss for the SFE but a gain for the central government and they are exactly the same, they cancel and do not impact social welfare in the case where the central government includes fine revenue. Social utility therefore is not impacted by the fine, whatever the size, because it represents a pure transfer from SFE to the central government. However, when the central government does not consider the fine revenue in their utility function, the mechanism design problem here implies this is only a loss for the SFE but not a gain to the central government. The term is not cancelled by the same term from the central government utility and it is still therefore present in the social welfare function.

To understand the first best case when the central government does not value fine revenue,

we define the social welfare function is:

$$SW = \bar{w} + b\left(1 - \frac{1}{\gamma(1-\tau)(Px - C(x))}\right) + Px - C(x) + S - x. \quad (2.29)$$

This is the perfect coordination scenario, where the central government has perfect information about the harvesting level. If the SFE harvests less than the harvesting limit, that is $x < \bar{x}$, they do not pay the fine, otherwise they will be fined. It is binary as we have perfect information now. In the first best solution, again, the harvest level chosen by the government is such that the fine is avoided because they want to maximize the social welfare. This is the same solution as the first best case when the fine is present in the central government's utility function.

Comparing first and second best, the social welfare loss is given by the following function of relevant parameters:

$$\begin{aligned} \bar{b}\left(\frac{1}{\gamma^0(1-\tau)(Px^0 - C(x^0))} - \frac{1}{\gamma^*(1-\tau)(Px^* - C(x^*))}\right) + Px^* - C(x^*) - (Px^0 - C(x^0)) \\ + \mu(x^0) - x^* + f\left(1 - e^{\bar{x}^0 - \mu(x^0) - \frac{\sigma_0^2}{2}}\right) + m(\sigma_0), \end{aligned} \quad (2.30)$$

where γ^0 , x^0 , γ^* , x^* and σ_0 are solved from the corresponding first order conditions.

Chapter 3

Data and Simulation Results

We now turn to examining the various cases above and social welfare losses for data related to China's Northeast collection of SFEs. This data relies on well-known and peer-published surveys designed and collected by the Environmental Economics Program in China (EEPC) at Peking University. The data set is combined with satellite vegetation coverage data from NASA to measure actual harvesting level and compare it to the central government quota for each SFE. Stated harvesting reported by SFE managers to the central government is falsely reported to equal the quota.

We simulate all decisions and choices by central and provincial governments, and the representative SFE manager. This is used to compute a value of the social cost of fiscal federalism in Northeast China by considering the loss in total social welfare under the first best case due to incentives that do not align for the SFE manager and the two principle governments that cannot perfectly observe actions of any other agent. A sensitivity analysis is used to explore possible ways to lower the social welfare losses by understanding how various aspect of the problem change under parameter changes. And, finally, we use a regression analyses to understand the most statistically significant factors of social costs holding other parameters constant. The purpose of this regression is not as a predictive model in the classical sense, but rather to show what correlations between parameters and data are important, and to identify the direction of these correlations and magnitude of the effects for each important variable while controlling for other variables. The specification of the regression will follow

the social cost definitions presented in the previous sections.

3.1 Data

Our data is from a survey conducted by the Environmental Economics Program in China (EEPC) at Peking University. This survey covers 24 randomly selected SFEs in the northeast of China. They are located in three provinces (Heilongjiang, Inner Mongolia and Jilin) shown in the following map.

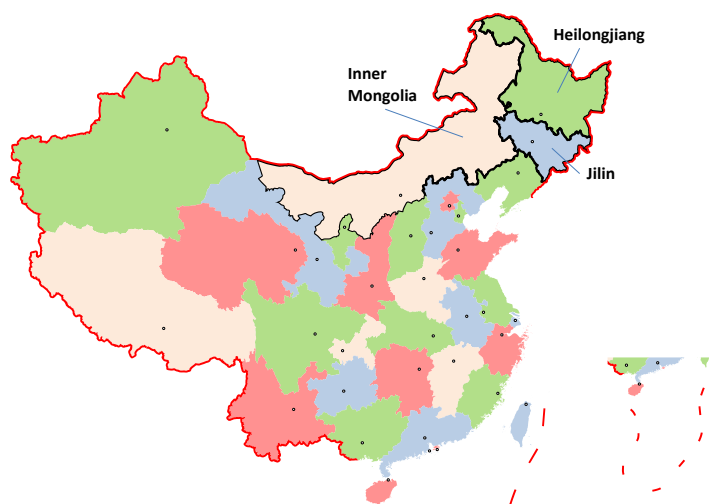


Figure 3.1: Jilin, Heilongjiang and Inner mongolia

The primarily harvested tree species in these provinces are Dahurian larch, white birch, Mongolian oak and spruce. The survey is collected for the period of 1980-2008. The survey consists of two waves, the first one in 2005, the second one in 2009. The data we use include SFE expenditure, timber price, primary industry production value and self-reported SFE timber harvesting level. Interviews with local officials indicated that promotion benefits for an SFE manager averages 20 percent of wage increases. We also use inflation data for China from the World Bank for deflation in order to restate all monetary data in

comparable form. Because prices are not generally available for SFE harvesting, and are not present in the Peking University survey, we use an average price of standing southern pine from Timber-Mart South 1st Quarter 2019 Vol.44 No.1 report and the cut-and-load cost average of southern pine from Joseph and Dahlen (2019) to estimate our cost-price ratio in the simulation model as 54.11 %. We use monitoring enforcement cost report from the International Tropical Timber Organization (ITTO) to calibrate the monitoring cost in our simulation model. Finally, we use self-reported timber harvesting level as the quota for the SFE, because it is well known that they overharvest but underreport at the required limit to avoid fines.

To ensure accuracy of the data., we dropped obvious (and probably misreported) outliers, and SFEs with missing data, so that we require as little simulated data as possible. As a result, we were left with twenty SFE cases for our simulation. These cases include a range of SFE sizes and differing distances from the central government. Table 3.1 presents a summary of all parameters and choices in the simulation.

3.2 Simulation results

To compute a value for the social cost of fiscal federalism, we solve the system of equations from the theoretical model in both first and second best cases. Then we calculate the social welfare loss according to equation (2.24); note that the reduction in social welfare amounts to the reduction of social welfare when evaluated at the first best optimal choices.

A summary of these results is shown in Table 3.2. In the table we calculated the optimal harvesting level for each SFE (x), the percentage of the transfer (γ), the socially optimal harvesting level (x_s), the socially optimal percentage of transfer (γ_s); and the social welfare loss (swl). The social welfare loss is deflated to year 2008 values.

Table 3.1: Summary of parameters and choice variables in the simulation

variable	notation	range
net promotion benefit	b	0.2517-19 (10000 yuan)
transfer percetage from SFE to local government	γ	To be solved in the model
tax rate for SFE	τ	0% to 1077%
timber price	P	0.00572-55 (10000 yuan)
cost function	$C(x)$	Take as 0.5411P
actual harvest level	x	To be solved in the model
central government signal of harvesting	$\mu(x)$	0.6x
harvesting limit	\bar{x}	8900-622720 (m3)
central government signal deviation	σ	Calibrated as 237
SFE expenditure	G	0-11795.69 (10000 yuan)
the upper limit for net promotion benefit	\bar{b}	1.2b
fine if overharvesting is caught	f	To be solved in the model
monitoring cost function	$m(\sigma)$	2.8 (10000 yuan)
SFE profit	π	28-52788 (10000 yuan)

*Ranges in parameters are explored with sensitivity analysis presented after the base simulation solutions.

Table 3.2: Simulation results for SFEs (first column) in Northeast China

SFE	year	$x(m^3)$	γ	$xs (m^3)$	γs	swl (1000 \$)
Heilongjiang Dahailin	2008	799923.3	0.975741	31380.69	0.573079	625992.3969
Heilongjiang Dongjingcheng	2004	860875.3	0.771537	49934.73	0.094859	762984.8969
Heilongjiang Hebei	2008	331989.2	0.724439	49992.37	0.09972	206568.7075
Heilongjiang Jinshantun	1990	412147.7	0.799559	49756.44	0.091909	703426.5056
Heilongjiang Jinshantun	1995	222365.4	0.761362	49756.44	0.094789	159606.2747
Heilongjiang Jinshantun	2000	127139.2	0.140109	49878.07	0.094606	45410.88563
Heilongjiang Langxiang	2008	331989.2	0.35145	49939	0.094732	207189.1097
Heilongjiang Qinghe	2008	182269.7	0.654014	50000	0.1	78890.50753
Heilongjiang Zhanhe	2000	855656.2	0.874659	49939	0.09738	810468.8116
Jilin Linjiang	2000	253924.5	0.538747	49878.07	0.094261	177207.4956

(To be continued)

SFE	year	$x(m^3)$	γ	$xs (m^3)$	γs	swl (1000 \$)
Jilin Linjiang	2008	199673.7	0.021755	49969.49	0.097606	94459.13514
Jilin Wangou	1995	682967.1	0.967328	34867.54	0.629853	709117.2784
Jilin Wangou	2004	568360.4	0.764478	49939	0.09673	474900.7014
Jilin Dunhua	2000	370157.2	0.68154	49939	0.097117	295593.736
Jilin Dunhua	2004	272358.5	0.468511	49939	0.096457	183279.0692
Jilin Dunhua	2008	802110.7	0.811406	49984.74	0.099077	584437.1592
Jilin Tianqiaolin	2008	148905.4	0.895419	22876.25	0.315272	91087.24067
Inner Mongolia Genhe	2000	935377.5	0.727074	49615.72	0.060453	898450.155
Inner Mongolia Genhe	2004	750294.5	0.723766	49847.64	0.087327	667033.4082
Inner Mongolia Genhe	2008	393719.1	0.216355	49867.12	0.08354	262563.1726

*The term x is the optimal harvesting level for each SFE; γ is the percentage of the transfer; xs is the socially optimal harvesting level; γs is the socially optimal percentage of transfer; and swl is the social welfare loss.

In the table, we compute the value of the social costs caused by the incentive incompatible problem and we investigate factors that influence these costs in the following sensitivity and regression analyses. We see that the SFE optimal harvesting level is higher than the socially optimal harvesting level for all of the SFEs here, which highlights the hidden actions mechanism design problem and the fact that all parties do not have incentives to perfectly cooperate. The SFE percentage of transfer is higher than the socially optimal percentage of transfer, because the social optimum requires that harvesting is lower due to benefits of the standing forest stock in the central government's social welfare function. This means SFEs always will overharvest and transfer more to the provincial government in exchange for a higher chance of promotion.

Our simulation therefore shows what has been generally known and argued in the literature, albeit without formal evidence. The table shows the social welfare losses (*swl*) due to these disincentives and the resulting second best outcome. Referring to social welfare losses, we see that they range between 45.41 million dollars to 898.45 million dollars. There are five SFEs with observations of more than one year.¹ We see the social welfare loss decreases over time. For example, for Heilongjiang Jinshantun, the loss was 703.43 million dollars in 1990 and decreased to 45.41 million dollars in 2000. This finding confirms that state forest reforms decreased some of the social welfare loss. However, more needs to be done. The social welfare loss is higher for those larger size SFEs, such as Inner Mongolia Genhe (632424 hectares) and Heilongjiang Dongjingcheng (266310 hectares). We also see a higher loss in SFEs with the furthest distance to Beijing, such as Heilongjiang Zhanhe (1320 kilometres) and Inner Mongolia Genhe (1243 kilometres). These SFEs are far away from the central government and harder to be monitored accurately. Inner Mongolia Genhe has 23 % of mature natural forest (in terms of area) in 2000. Jilin Wangou has 12 % of mature natural forest (in terms

¹These are Heilongjiang Jinshantun, Jilin Linjiang, Wangou, Dunhua, and Inner Mongolia Genhe.

of area) in 1995. Large percent of mature natural forests also makes it harder to do accurate monitoring. Therefore, the SFEs harvest over the limit with a very low probability of being fined. We will show this further in the following sensitivity analysis and regressions.

3.3 Sensitivity analysis

To explore possible ways to lower the social welfare losses and to examine how parameters impact these losses, we now conduct a sensitivity analysis of key parameters. We examine each parameter with a percentage change of -20%, -10%, 0%, 10%, and 20% around our assumed or observed values (thus, 0% represents the case we used in the Table 3.2 results), we then solve the first and second best problems and the social welfare loss under each shift in parameters focusing on each parameter separately.

We present these results in a series Figures 3.2 - 3.11. In the figures, each of the colored lines represents a different SFE in the sample and we pick five representative SFEs for illustration². The x axis is the percentage changes of the variable we are conducting sensitivity analysis for, and the y axis is the social welfare loss, SFE harvesting level or SFE percentage of transfer to the provincial government depending on the figure. The patterns in the figures therefore show what happens to the Y axis variables from 20% smaller to a 20% higher value of each parameter given on the X axes. The 0 line on the Y axes refers to the base simulation case in Table 3.2. Thus, reading across the X axis and noting where on the Y axis each line is located indicates how the variable of interest depends on variations in the X axis parameter.

²These are Heilongjiang Dahailin 2008, Heilongjiang Jinshantun 1995, Jilin Linjiang 2008, Jilin Wangou 1995, and Jilin Dunhua 2004 from Table 3.2. These are representatives of all the patterns observed in SFEs for the sensitivity analyses.

3.3.1 Sensitivity analysis of the social welfare loss

Figure 3.2 represents the sensitivity analysis of the social welfare loss to the harvest quota, \bar{x} , which is our main focus. There is roughly an upward trend in social welfare losses as the percentage change in the harvesting limit increases. These results support the argument that an increased social welfare loss (*swl*) is always expected if the central government relaxes the quota (\bar{x}). This is intuitive, as a higher harvesting limit allows more harvesting, and this results in lost public goods values from the forest stock. The jagged nature of some of the graphs could be partially explained by the term $\bar{x} - x_s$ in the SFE utility function (equation 2.3). Although SFEs typically harvest over the harvesting limits, the actual harvesting level can differ and depend on the parameters being investigated in the sensitivity analysis. Therefore, the harvesting signal x_s can be higher or lower than the harvesting limit \bar{x} . This may cause some of the jagged features in the graph.

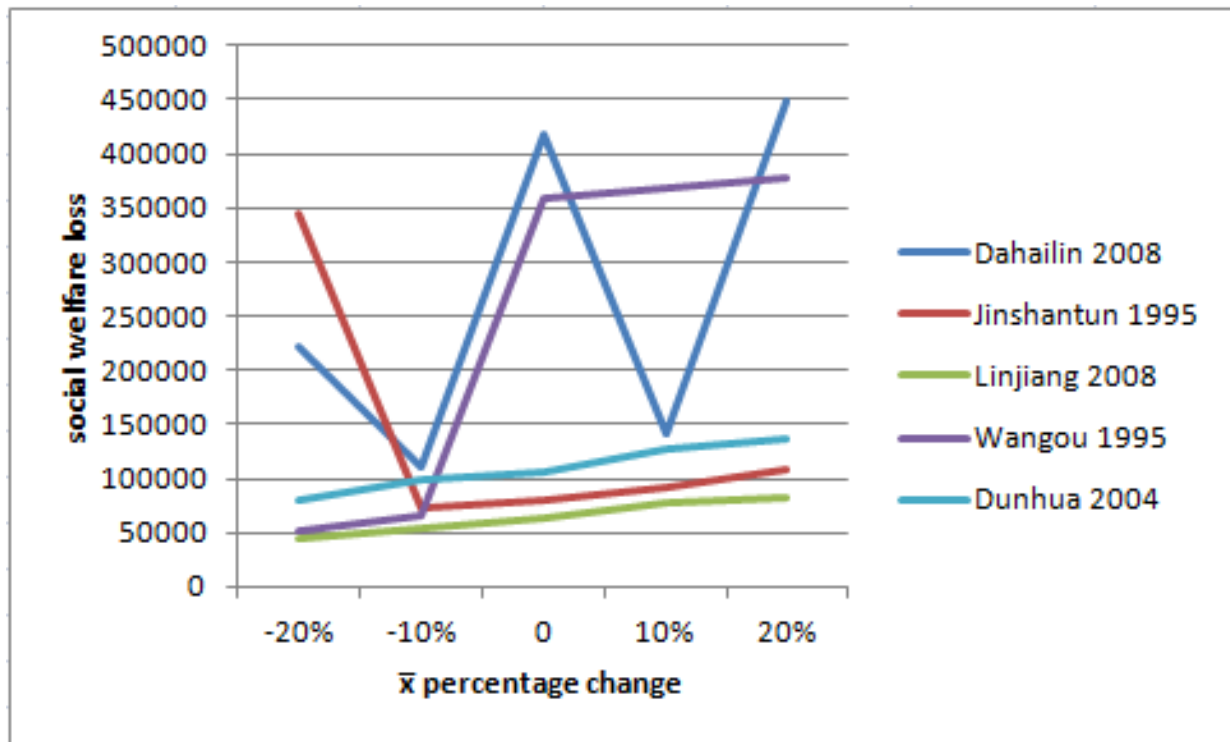


Figure 3.2: Sensitivity analysis of \bar{x} for the social welfare losses

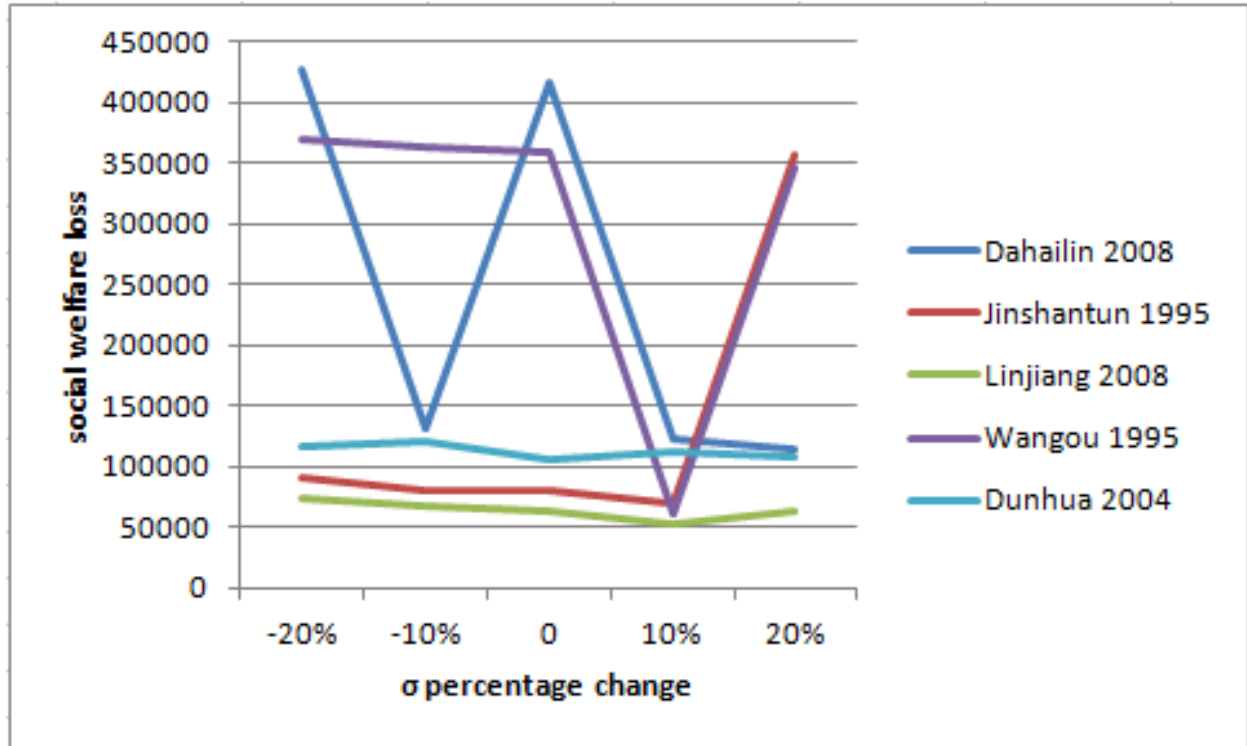


Figure 3.3: Sensitivity analysis of σ for the social welfare losses

Figure 3.3 considers sensitivity in the standard deviation of the monitoring signal received by the central government (σ), from equation (2.2). Although the trends are different for different SFEs at different percentage changes of σ , we can roughly see several upward trends reading from left to right, especially in the 0% - 20% increase part of the X axis. The social welfare loss (swl) increases with the monitoring signal standard deviation (σ), because it is easier for SFEs to overharvest as inaccuracies in monitoring become larger. In terms of social welfare loss, some SFEs are not affected by the change of σ and appear as flat lines in the graph, while other SFEs have a “W” shaped trend with some upward and some downward trends at different percentage change of σ . A larger standard deviation allows the signal to be higher or lower, thus the effects differ across SFEs. Our regression data will explore this parameter further.

In equation (2.2), recall that μ is the fraction of SFE harvesting that is monitored by the

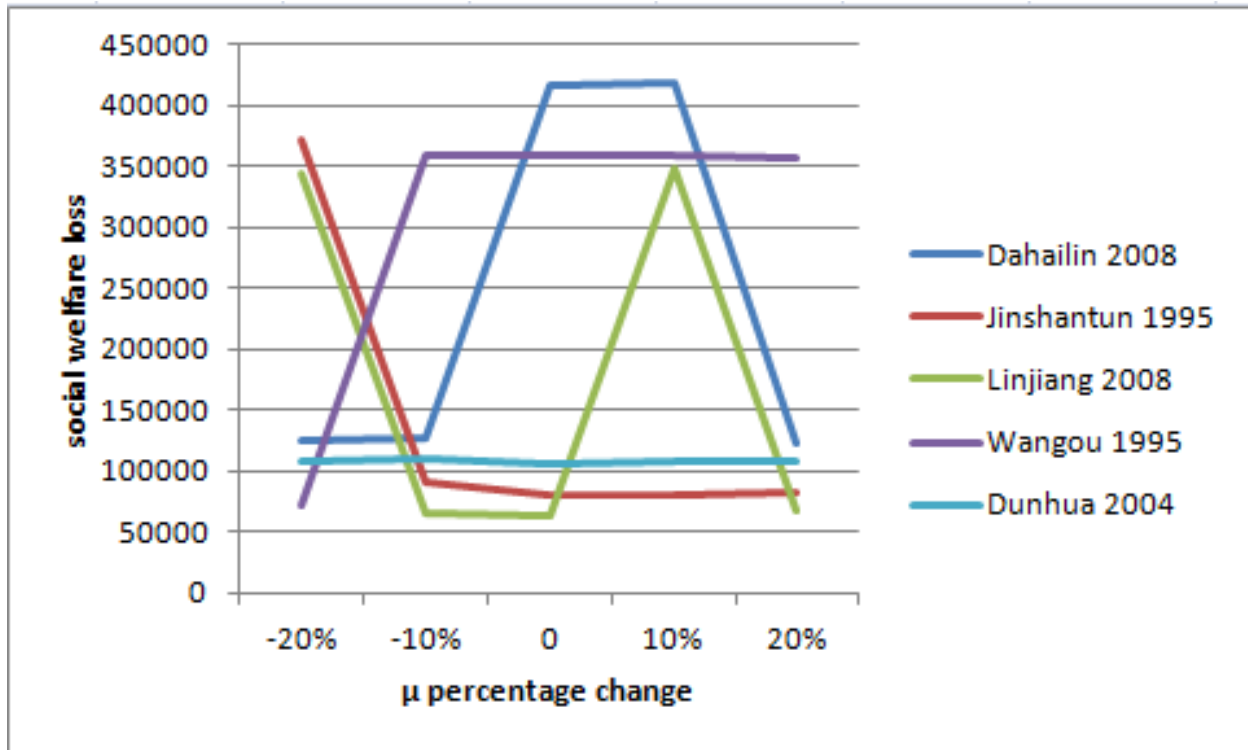


Figure 3.4: Sensitivity analysis of μ for the social welfare losses

central government in the harvesting signal function. Figure 3.4 shows our results concerning the sensitivity analysis of μ . Overall, we see that the social welfare loss (*swl*) decreases with increases in μ for several SFEs. For different SFEs, the decreasing trend happens at different percentage changes of μ . A higher μ means more harvesting can be monitored, thus the SFE harvesting level is lower and the social welfare loss is lower. This is intuitive, as the higher the monitoring accuracy is, the lower the social welfare loss must be (shown also in Figure 3.3).

Summarizing, from the sensitivity analyses of the social welfare loss in Figures 3.2 - 3.4, the key to lowering this loss appears to be improving the quality of monitoring and imposing stricter harvesting limits or quotas on the part of the central government. Put another way, increasing the efficiency of enforcement is clearly required to achieve incentive compatible deforestation limits in Northeast China and move the federalism outcomes closer to first best

outcomes.

3.3.2 Sensitivity analysis of the SFE harvesting level

The next decision of interest in our sensitivity analysis is that of the SFE actual harvesting level (x). Figure 3.5 presents results for the effect of the harvest limit (quota) parameter on actual SFE harvesting. As expected the figure shows an upward trend in x as the harvest limit increases in magnitude. That is, x increases with harvesting limit (\bar{x}). As we saw above, this is important to increases in social welfare as the harvest level becomes even further above the socially optimal level when the harvest limit is relaxed. Referring to Figure 3.5, the sensitivity analysis of \bar{x} for swl and x have a similar trend as in Figure 3.2.

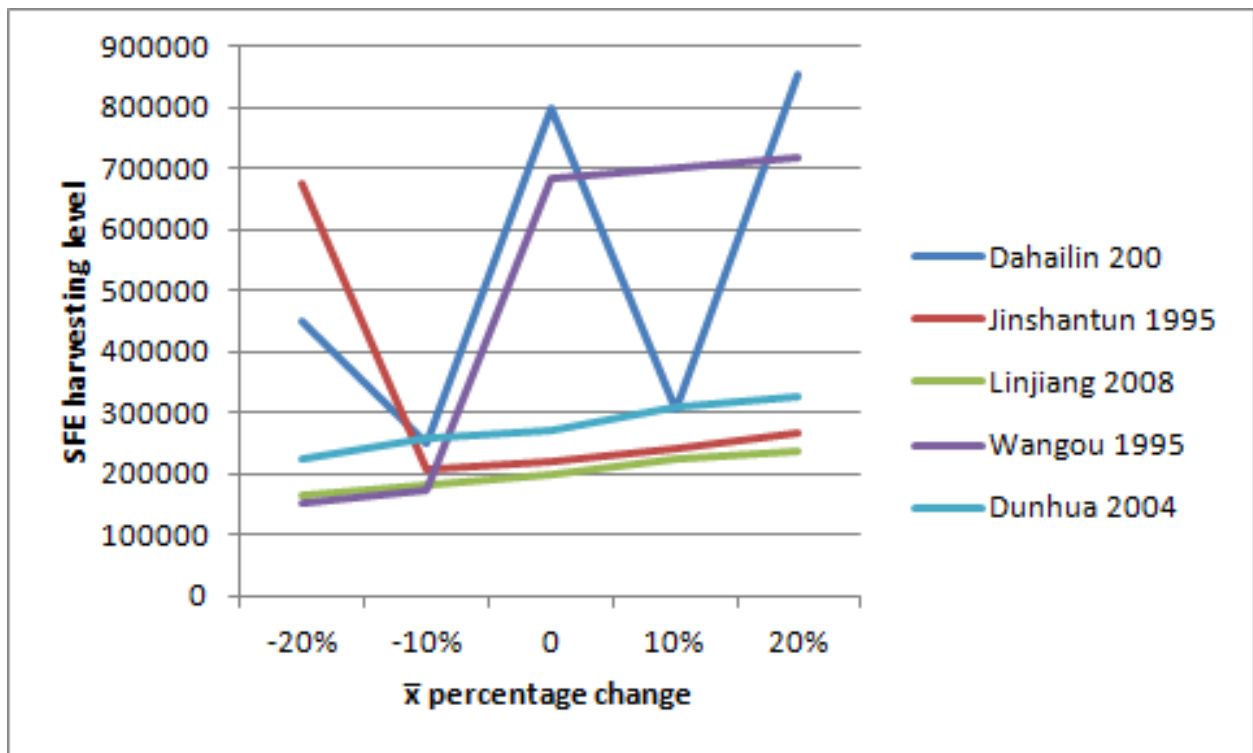


Figure 3.5: Sensitivity analysis of \bar{x} for the SFE harvesting level

Figure 3.6 presents the sensitivity analysis of the standard deviation of the monitoring signal

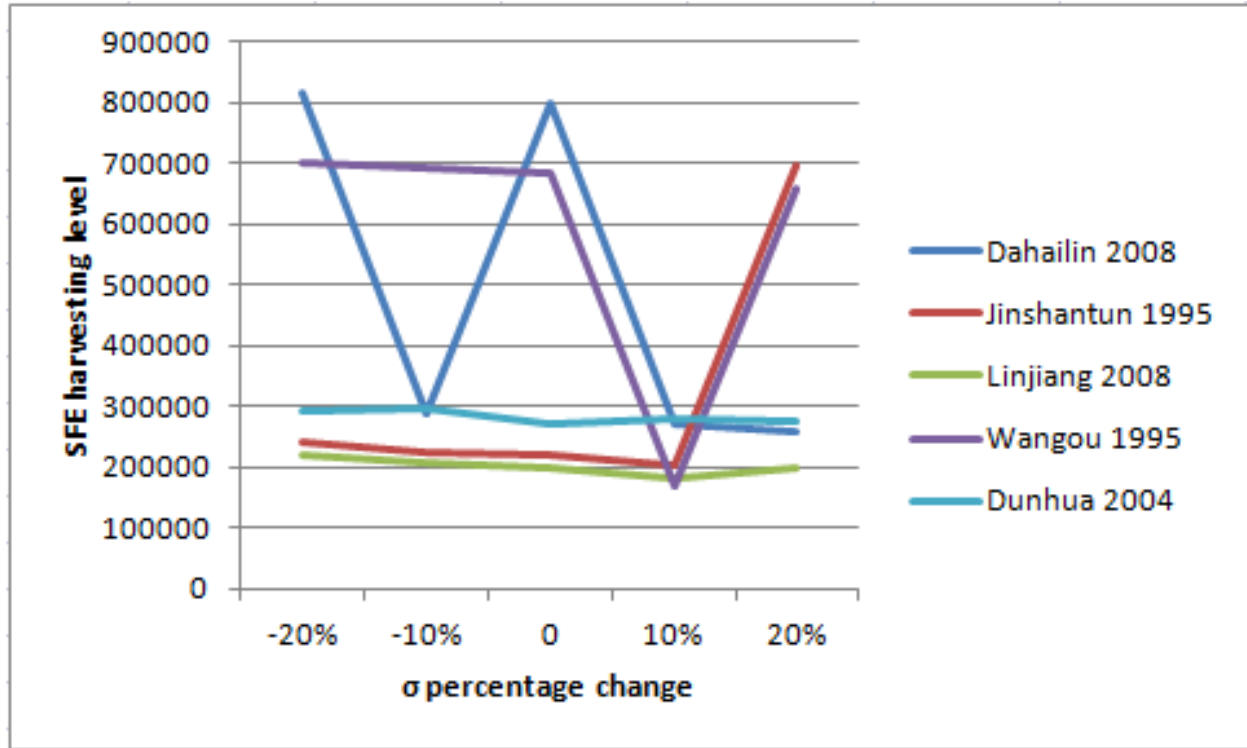


Figure 3.6: Sensitivity analysis of \bar{x} for the SFE harvesting level

(σ) on SFE actual harvesting. In general, we see an upward trend of the SFE harvesting level (x). That is, x increases with σ , especially at the 20% increase part. The increasing trends happen at different percentages for different SFEs. When σ is larger, the monitoring signal by the central government varies in a wider range, which leads to more room for harvesting over the limit without being caught. This variation can make the signal higher or lower, and explains the “W” shaped trend with some upward and some downward trend at different percentages. The sensitivity analysis of σ for swl and x have a similar trend as shown in Figures 3.3 and 3.6.

Figure 3.7 illustrates how the fraction of harvesting that is monitored by the central government in the harvesting signal function, μ , impacts SFE harvesting. The SFE harvesting level (x) decreases with increasing μ . μ is the fraction of harvesting that is monitored, so that a higher μ means more harvesting can be monitored. Therefore, the SFE harvesting level (x)

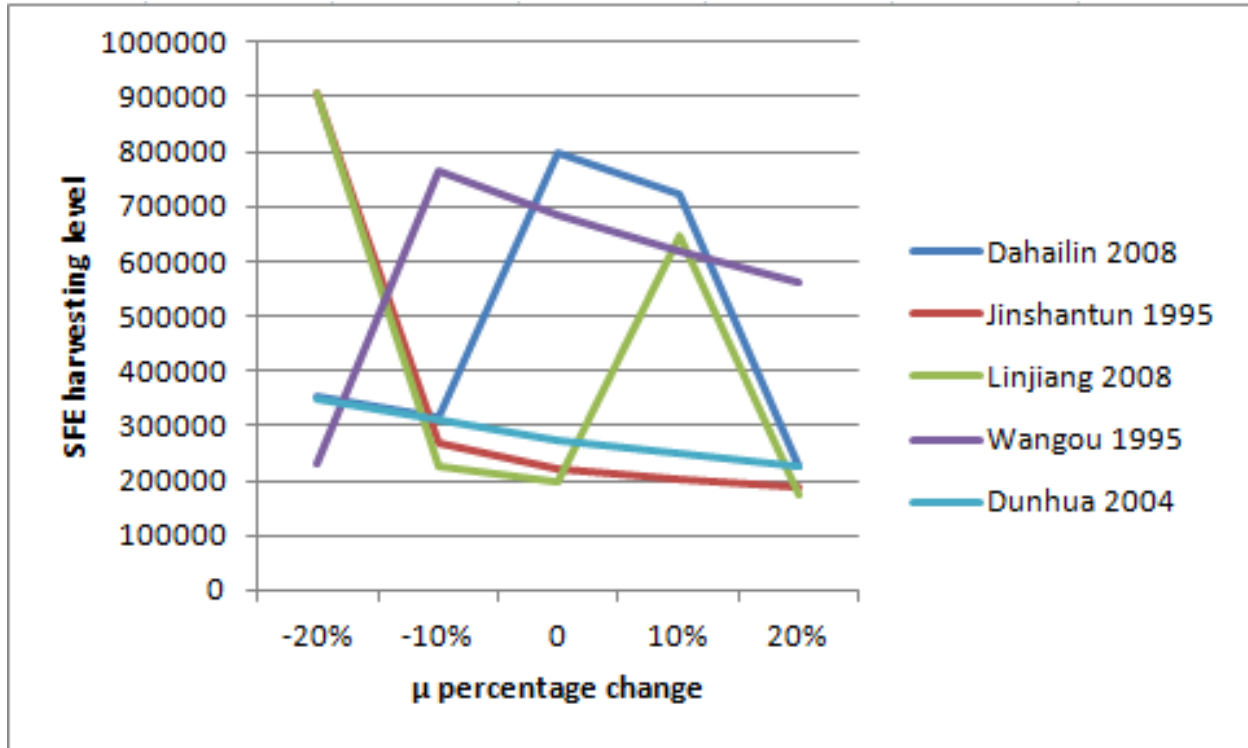


Figure 3.7: Sensitivity analysis of μ for the SFE harvesting level

is lower to avoid the higher risk of being caught.

In sum, we see a similar results concerning how the SFE choice of harvesting level and the social welfare losses depend on key parameters. This also shows how SFE harvesting levels (the amount of over-logging) are key contributors to social welfare losses. The sensitivity analysis indicates that parameters related to accuracy of law enforcement are critical to abating overharvesting within SFEs in Northeast China.

3.3.3 Sensitivity analysis of the SFE percentage of transfer

The percentage transfer to the SFE manager (γ) is also an important variable in the model. We now illustrate the key parameters affecting γ . Figures 3.8 - 3.11 illustrate sensitivity analysis for γ with respect to timber price (P), expenditure (G), harvesting limit (\bar{x}) and

harvesting cost (C).

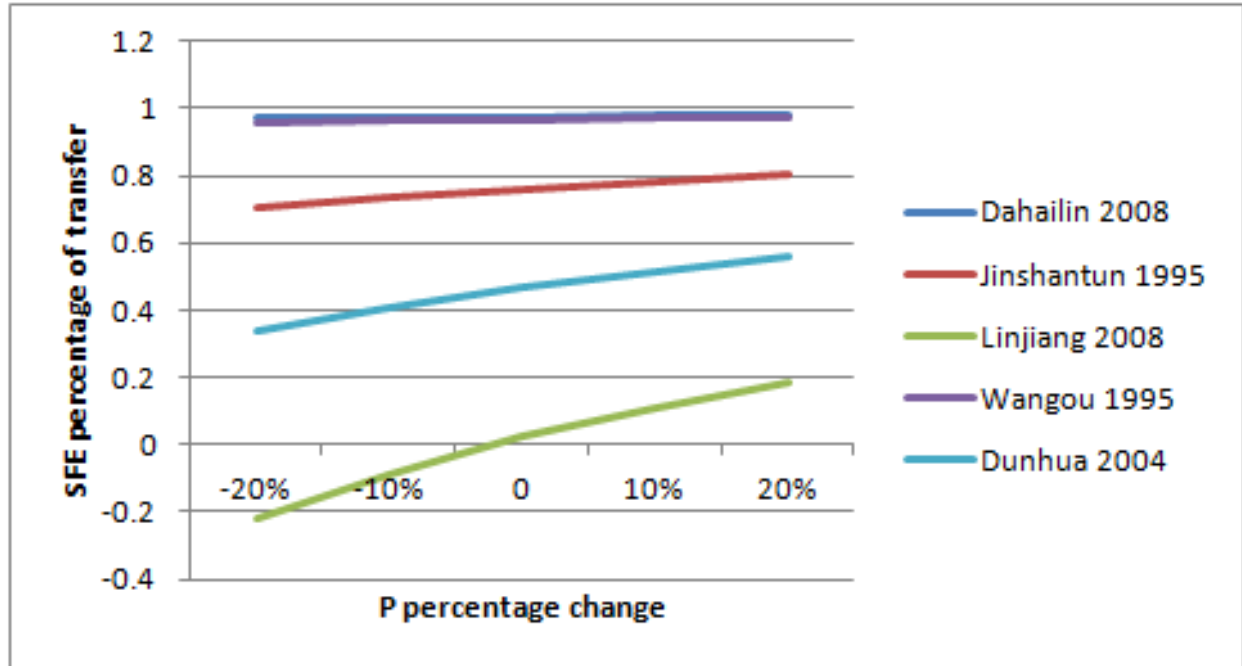


Figure 3.8: Sensitivity analysis of P for the SFE percentage of transfer

Figure 3.8 illustrated the sensitivity analysis of the timber price (P) for the SFE percentage of transfer (γ). There is an increasing trend, γ increases with P . The increasing trend is more significant for those SFEs with a relatively low transfer percentage. For those that have already transferred a larger percentage, there is not much room for increase. SFEs make more profit with a higher timber price. This allows them to cover their obligated expenditures for the local state enterprise community more easily and transfer more to the provincial government. The expenditure is fixed and the transfer amount is higher, thus the percentage of transfer is higher.

Figure 3.9 shows the importance of the SFE expenditure (G). There is a decreasing trend, with γ decreasing with SFE expenditure (G). A higher G indicates SFEs expend more for the local state enterprise communities, thus transferring less to the provincial government. The percentage of transfer is lower. The decreasing trend is more significant for those SFEs

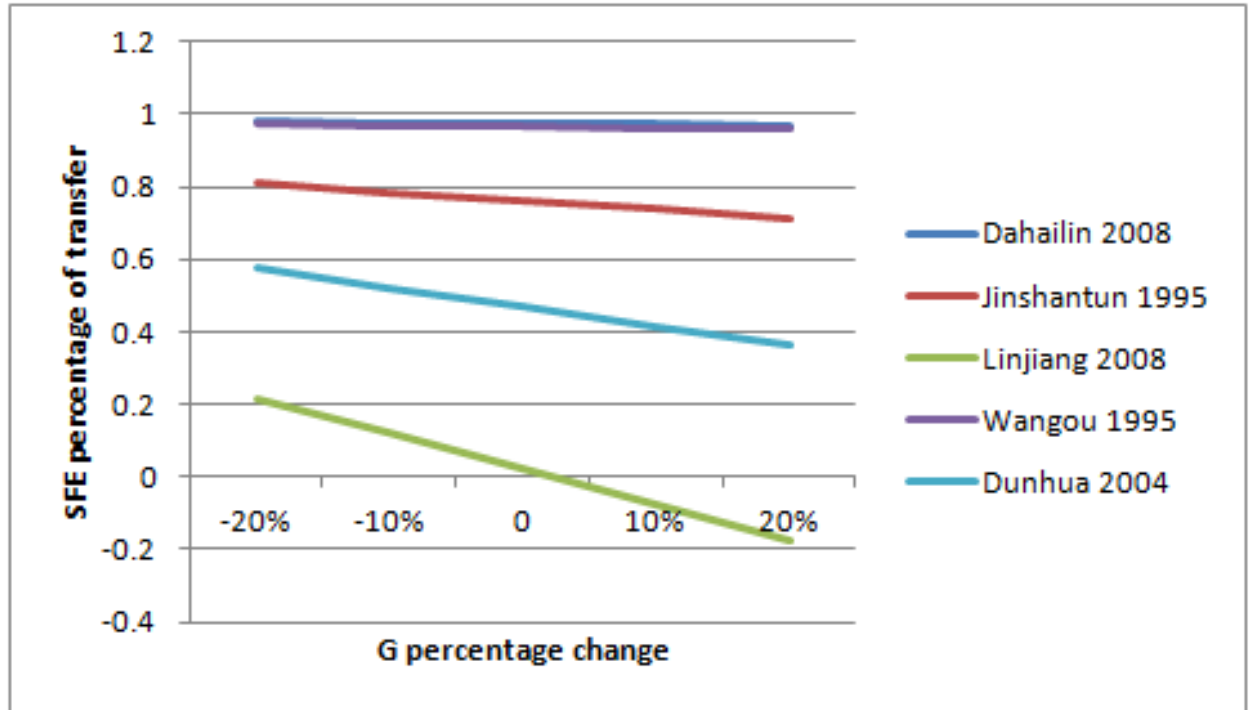


Figure 3.9: Sensitivity analysis of G for the SFE percentage of transfer

with a relatively low transfer percentage, as they barely cover the expenditure. For those that have already transferred a larger percentage, the expenditure is just a small fraction of their profit and the effect is less significant.

Figure 3.10 shows sensitivity analysis of the harvesting limit (\bar{x}). Overall, this is an upward trend. The transfer γ increases with the harvest limit (\bar{x}). A higher harvesting limit allows more harvesting, thus SFEs have incentive to transfer more to the provincial government. The increasing trend is more significant for those SFEs with a relatively low percentage of transfer. This is consistent with our previous analysis.

Figure 3.11 shows the sensitivity analysis of the harvesting cost (C); γ decreases with the harvesting cost. A higher C indicates SFEs have less profitable harvesting, thus providing greater incentives to transfer less to the provincial government. In the figure, this is more significant for those SFEs with relatively low transfer percentages. For those that already

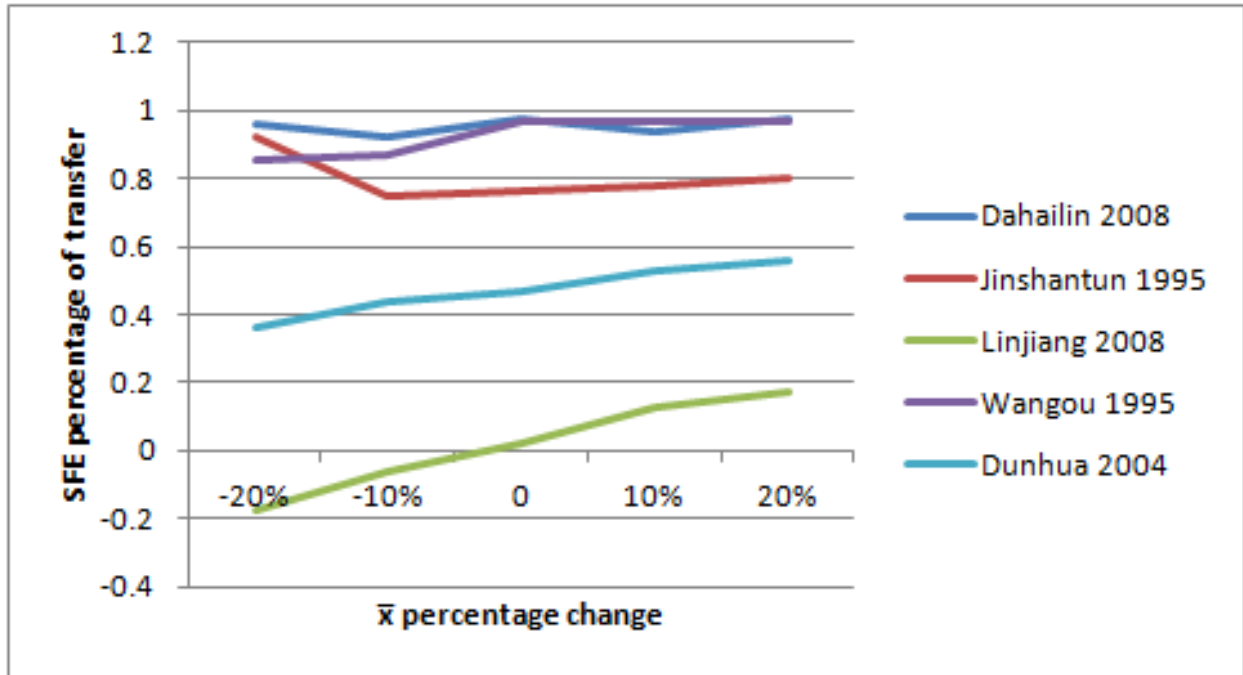


Figure 3.10: Sensitivity analysis of \bar{x} for the SFE percentage of transfer

transfer a larger percentage to provincial governments, an increase in harvesting cost is just a small fraction of their profit and the effect is less significant.

From the sensitivity analysis of the SFE transfer to provincial governments, we have two types of results. SFEs transfer a higher percent of their profit to the provincial government when their profits are higher, that is, when the timber price is higher or they are allowed to harvest more. In contrast, SFEs transfer a lower percent of their profit when their profits are lower, that is, when the harvesting cost is higher or they have greater costs to spend for the local state enterprise community.

3.3.4 Sensitivity analysis when fine revenue is part of social welfare

We briefly consider the case for social welfare losses where the central government does not include fine revenues in their utility function. We ran our simulation again and calculated the

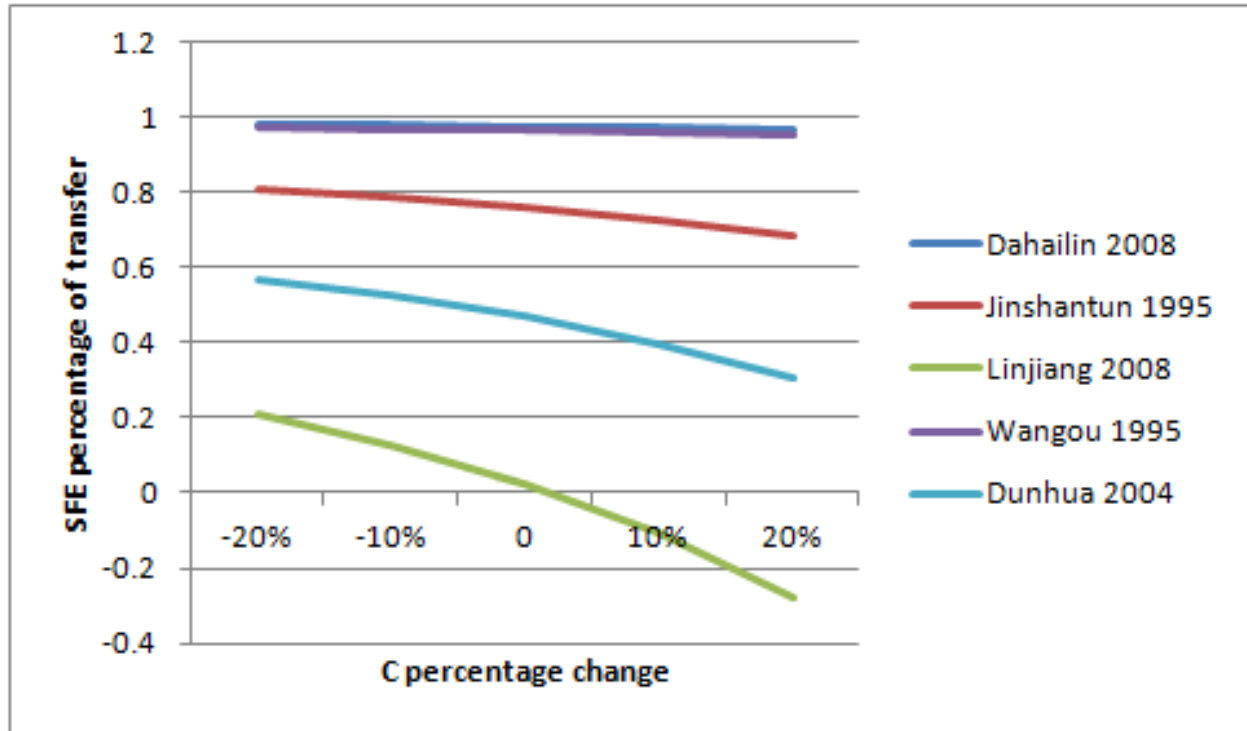


Figure 3.11: Sensitivity analysis of C for the SFE percentage of transfer

social welfare loss using equation (2.30). We repeated all the sensitivity analysis procedures discussed previously. In all the analyses, there are very similar results with Figures 3.2 - 3.11, The only difference worth mentioning is for the monitoring related variables μ and σ . The trends above are still the same as in Figures 3.2 - 3.3, but the magnitudes of the effect on social welfare losses are higher. Finally, we also find that the social welfare loss in equation (2.30) is lower than that of equation (2.24). Social welfare loss is lower when the central government does not value fine revenues in their utility function. This suggests that a central government who sets policy parameters based on revenue collections in the federalism case will ultimately lead to higher welfare losses following from disincentives of governments and SFE managers to perfectly coordinate.

Chapter 4

Econometric Results

To investigate the significance of factors that influence social welfare losses from deforestation in SFEs, we can regress the calculated social welfare loss on other variables collected in our survey. The purpose of a regression in this case is not to create a prediction model, but rather to identify the more important influences on social welfare loss variation, holding other effects constant.

4.1 Econometric Data

The data we use consist of a panel of 24 SFEs in the Northeastern China forest region from years 1980 to 2008 assembled in a stacked fashion. The social welfare loss is deflated to 2008 and recomputed in 1000s USD. This is denoted as `swl_df` and represents the dependent variable in our analysis.

Table 4.1 provides a summary of the descriptive statistics of all variables used in the regression. Explanatory variables are taken from parameter variables concerning the SFE managers; these includes the manager tenure experience (in years, denoted as `tenure_exp`), education level (in years, denoted as `edu`), and age (in years, denoted as `age`). The SFE manager is the key decision maker in the SFE, so their age, education level and tenure experience in the SFE affects the harvesting and transfer decision, and therefore is expected to factor into social welfare loss.

We also control for other SFE characteristics. These include the deflated SFE total social value (in 1000 USD, deflated to year 2008, denoted as `socialv_df`), total area (in hectares, denoted as `SFEtotalarea`) and number of SFE employees, denoted as `pop`). We also include the distance of each SFE from the central government. These are calculated using the longitude and latitude data of each SFE and Beijing (denoted as `s`, in kilometers). Using the area data of the forests, we calculate the percentage of the natural forest (denoted as `nat_per`) and the percentage of the planted forest (denoted as `pl_per`) in each SFE. We also calculate the percentage of juvenile forest and mature forest for both the natural and planted forests. Therefore we have juvenile natural forest percentage (denoted as `juv_per_area`), mature natural forest percentage (denoted as `mat_per_area`), juvenile planted forest percentage (denoted as `pl_juv_per_area`), and mature planted forest percentage (denoted as `pl_mat_per_area`). We also calculate these percentages both based on growth rates and based on area. Thus, for example, mature natural forest percentage calculated using growth data is denoted as `mat_per_growth`. The National Forest Protection Program (NFPP) was implemented in 2000 to protect the natural forest in Northeast China. Variables in the regression measuring this effect are the non-harvesting area required by the program (denoted as `noharv_per`) and the limited harvesting area allowed (denoted as `limitharv_per`) in the forests of SFEs. These variables will measure the impact if any of this program on social welfare losses from SFE deforestation. Finally, in order to increase the sample size to a sufficient size for regression analyses, we use the inflation adjusted timber price data to make up for the missing data in the following years. This allows more observations of the social welfare losses.

Table 4.1: Summary of the variables in the regression

Variable	Mean	Std. Dev.	Min.	Max.	N
swl_df	420902.673	468780.377	5399.568	3506226	99
tenure_exp	2.978	2.083	1	13	594
edu	5.397	1.709	1	9	594
age	141.359	282.406	35	999	594
socialv_df	65470.436	32931.458	19176.148	153445.047	42
pop	35773.775	11666.914	4323	62841	151
juv_per_area	0.202	0.159	0.004	0.813	154
mat_per_area	1.037	7.944	0	86.991	153
mat_per_growth	5.205	59.66	0	733.41	151
pl_juv_per_area	1.04	2.871	0.015	35.144	153
pl_mat_per_area	0.032	0.109	0	0.926	84
nat_per	0.849	0.792	0.201	8.91	130
pl_per	0.218	0.713	0.002	7.282	130
pop_des	0.202	0.176	0.016	1.642	117
noharv_per	18.813	54.32	0.059	343.727	41
limitharv_per	16.547	24.702	0.136	96.673	38
s	1181	149.487	909.318	1399.058	658
employee_struc	1.684	1.39	0.067	5.708	48

4.2 Regression results

Table 4.2 presents results by regressing social welfare losses (first row variable in Table 4.2) for each SFE on explanatory variables (all other rows in Table 4.2), and for five specifications (models 1 - 5). The number of explanatory variables vary by specification in the table, as do the number of observations. It turned out that timber price has little variation across SFEs given that markets for timber are complete in Northeast China. While stumpage price would vary based on terrain and location, the mill or gate price that we have data on would not vary over SFEs since multiple SFEs supply the same mills. Referring to the specifications in Table 4.2, model 1 controls for SFE characters using total value and population; model 2 adds SFE total area; in model 3 we include more SFE characteristic variables. Based on model 1, we include SFE manager tenure experience, education and age of the manager, as

these factors are shown to be important by Li and Zhou (2005). We also include the distance of the SFE to the central government. Because Xu, Tao, Amacher (2004) found that the remote area are harder to monitor. This also tests the robustness of the positive correlation between the mature natural forest percentage and the social welfare loss in model 1. Model 4 adds SFE mature natural forest growth variables to the specification, as it is identified to be a key contributor to deforestation by Xu, Tao, Amacher (2004). Finally, model 5 adds juvenile planted forest growth variables to the specification. The number of observations overchange across specifications due to dropping of missing data.

Referring to the results, we see that there is a significant positive correlation between the social welfare loss and the mature natural forest percentage, no matter whether it is calculated by growth or area. In model 1, each one percent increase of the mature natural forest increases social welfare loss by 21 million US dollars. In model 3, each 1 percent increase of the mature natural forest increases 32 million US dollars of social welfare loss. In model 4, the percentage is calculated by growth: here, a one percent increase of the mature natural forest increases social welfare losses by 26 million US dollars. This shows robust positive correlation between the social welfare loss and an SFE mature natural forest percentage, and may indicate areas of SFEs where the government needs to monitor more heavily if reductions in social costs are to be afforded. One problem with this, and a reason for the results, is that others have argued that it is more costly and difficult for the central government to monitor in natural forested areas when they make up a larger percentage of the SFE forested area (Xu, Tao, and Amacher 2004, Yi, Habla, and Xu 2017). Our new finding is that, regarding the contribution to the social welfare loss, mature forested area is especially significant and cannot be ignored moving forward.

We also find a significant positive correlation between the social welfare loss and SFE total area in model 2. One more hectare of total area results in an increase of 1214 dollars in

Table 4.2: Regression results of social welfare loss as dependent variable

	(1)	(2)	(3)	(4)	(5)
	swl_df	swl_df	swl_df	swl_df	swl_df
mat_per_area	2115658.7** (2.85)		3220133.8* (2.68)		
socialv_df	-5.931* (-2.18)	-4.222 (-0.70)	-10.43 (-1.64)	-10.26 (-1.59)	-3.261 (-0.48)
pop	-6.930 (-1.09)	-0.0134 (-0.00)	-0.867 (-0.08)	1.385 (0.13)	0.0907 (0.01)
SFEtotalarea		1.214* (2.19)			
tenure_exp			70164.7 (1.32)	64731.0 (1.21)	100401.1 (1.63)
edu			-29575.5 (-0.27)	-36496.0 (-0.32)	13121.5 (0.11)
age			-13647.6 (-0.47)	-12275.8 (-0.41)	-13619.1 (-0.42)
s			2700.3* (2.69)	3122.4** (2.93)	3515.6* (2.89)
mat_per_growth				2591090.6* (2.56)	
pl_juv_per_growth					-1779740.3* (-2.27)
Constant	935579.9 (3.20)	503754.0 (1.12)	-1641452.7 (-0.86)	-2233757.2 (-1.17)	-2220517.1 (-1.09)
Observations	42	27	24	24	23

t statistics in parentheses,

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

social welfare loss. A possible explanation is the larger SFEs are harder to monitor. This is consistent with the finding by Xu, Tao, Amacher (2004) that the larger size SFEs have a greater reduction in forest growth rate. There is also a significant positive correlation between the social welfare loss and distance to the central government(s). This indicates that when the SFE is further away from the central government, the social welfare loss is higher. One kilometer away from the central government results in either a 2.7 or 3.1 million dollars increase in social welfare loss in model 3 and 4, respectively. One explanation for this is the monitoring cost is higher for these remote SFEs.

We find a significant positive correlation between the social welfare loss and the SFE total social value in model 1. However, this is not robust in model 2,3 and 4. We also find positive correlation between social welfare loss and SFE employee structure. The employee structure is calculated using the number of employees divided by the total number of laid-off people and retired people. Finally, and interestingly, we found no significant impact of the harvesting area and limited harvesting area set by the National Forest Protection Program. This is not surprising given that this program does not address the federalism and disincentives of governments and SFE managers we have uncovered in this story.

In model 5, the results show a negative correlation between the social welfare loss and juvenile planted forest percentage (calculated by growth). Planted forest has a lower monitoring cost, thus has less overharvesting.

Chapter 5

Conclusions

We developed a two-principal, one-agent model to describe the incentive incompatibility problem inherent in forest harvesting decisions by state forest enterprises in Northeast China. A key part of our approach is to characterize a social welfare loss from failures of state forest managers to coordinate with provincial and central governments, as well as the different incentives for use of state forests faced by provincial and central governments.

The model reveals key differences in first and second best harvesting outcomes that are realized in social welfare losses. These losses are social costs of harvesting outcomes that do not align incentives of the state forest enterprise manager and the two governments. The model also shows the difficulty in one principle (the central government) setting a harvesting quota and enforcement strategy to achieve the first best outcome given the importance of the lower level provincial government in state forest enterprise manager decision making. There is no work we are aware of that examines these issues for the large forest regions of China; yet continued deforestation there is of world interest.

Using our framework, we use published data to compute social welfare losses from deforestation for different sized state forest enterprises in four northeastern Chinese provinces, and we examine the sensitivity of these losses to various parameters related to financial incentives for harvesting, monitoring and enforcement costs by the central government, transfer parameters from state forest enterprises to local governments, and harvesting limits or quotas set by the central government. Finally, a regression analyses is used to assess the nature of significant

factors of social welfare losses controlling for other variables.

We find that social welfare losses depend critically on state forest size, distance from the central government, and various central and provincial government policy instruments. Sensitivity analysis to investigate the major contributors to social welfare loss identifies that lower harvesting limits and a more accurate monitoring system are the two key factors to lowering these losses. Consider harvesting limits as carrot and the monitoring system as stick, this is a carrot-stick result that is common in second best problems (Balch 1980, Henderson et al. 2013, Duchelle et al. 2017). It is logical to combine lower harvesting limits with a monitoring system that reduces variability in signals of harvesting that the central government receives from state forests. Regression results are also consistent with this basic finding, indicating that the remote areas with a higher percentage of mature natural forests are the ones with the highest social welfare loss.

All our findings here suggest that monitoring is the key to lowering the social welfare loss and resolving the federalistic incentive incompatible problem that we have shown characterizes state forest harvesting in China. We present two possible solutions. The first is to decentralize the monitoring to the provincial government levels. It is also suggested by Xu, Tao, Amacher (2004). Although they did not examine social welfare losses, they nonetheless conclude based only on remotely sensed harvesting rates that decentralizing forest management and enforcement as much as possible reduces wedges in incentives among agent and principles. In many ways we have rigorously shown that their suggestion is correct. Because state forests are fixed entities, the monitoring cost is lower for local governments, and they also have better information on local forest stocks that can be used to set more incentive-compatible harvest standards. This would lessen the social welfare losses attributed the incomplete information problem that currently now exists. Also, decentralization would provide local governments with additional incentives to monitor and protect forests. With regard to monitoring, our

results suggest that less costly and emerging technologies, such as drones could be highly important to lower social costs throughout China's largest wood basket.

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Appendices

Appendix A

Regression code using STATA

```
clear use data.dta drop if swl_df < 0 gen swl_df_wanyuan=swl_df replace swl_df=1.5*swl_df_wanyuan
gen socialv_qianyuan=socialv gen socialv_df=0.15*socialv_qianyuan*deflator
sum swl_df tenure_exp edu age socialv_df pop juv_per_area mat_per_area mat_per_growth
pl_juv_per_area pl_mat_per_area nat_per pl_per pop_des noharv_per limitharv_per s
employee_struc
sutex swl_df tenure_exp edu age socialv_df pop juv_per_area mat_per_area mat_per_growth
pl_juv_per_area pl_mat_per_area nat_per pl_per pop_des noharv_per limitharv_per s
employee_struc, lab nobobs minmax
reg swl_df mat_per_area
reg swl_df mat_per_growth
reg swl_df pl_juv_per_growth
reg swl_df pl_per
reg swl_df pop_des
reg swl_df employee_struc
reg swl_df mat_per_area socialv_df pop estimates store m1, title(Model 1)
reg swl_df SFEtotalarea socialv_df pop estimates store m2, title(Model 2)
```



```

reg swl_df mat_per_area socialv_df pop tenure_exp edu age s estimates store m3, title(Model
3)

reg swl_df mat_per_growth socialv_df pop tenure_exp edu age s estimates store m4,
title(Model 4)

reg swl_df pl_juv_per_growth socialv_df pop tenure_exp edu age s estimates store m5,
title(Model 5)

reg swl_df pl_per socialv_df pop tenure_exp edu age s estimates store m6, title(Model 6)

estout m1 m2 m3 m4 m5 m6, cells(b(star fmt(3)) se(par fmt(2))) /// legend label varlabels(_cons
constant) /// stats(r2 df_r bic, fmt(3 0 1) label(R-sqr dfres BIC))

estout m1 m2 m3 m4, cells(b(star fmt(3)) se(par fmt(2))) /// legend label varlabels(_cons
constant) /// stats(r2 df_r bic, fmt(3 0 1) label(R-sqr dfres BIC))

eststo: quietly regress swl_df mat_per_area socialv_df pop eststo: quietly regress swl_df
SFEtotalarea socialv_df pop eststo: quietly regress swl_df mat_per_area socialv_df pop
tenure_exp edu age s eststo: quietly regress swl_df mat_per_growth socialv_df pop tenure_exp
edu age s eststo: quietly regress swl_df pl_juv_per_growth socialv_df pop tenure_exp edu
age s eststo: quietly regress swl_df pl_per socialv_df pop tenure_exp edu age s esttab using
t1.tex, label nostar /// title(Regression table)

sort fbid year sum year count if year==2008

```

Appendix B

Sensitivity analysis code using Mathematica

```

data=Import["C:\\Users\\lenovo\\Desktop\\basedata2021.2.20.csv"];

swlcompute[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_]:=Module[{vG,v
\[Tau],vP,vb,vxbar,v\[Sigma],x,\[Gamma],f,bbar,xs,\[Gamma]s,d,cswl,vc,vmu,
amen},

vG=G;

v\[Tau]=\[Tau];

vP=P;

vb=b;

vxbar=xbar;

v\[Sigma]=\[Sigma];

vc=c;

vmu=mu;

amen=1;

d=Range[5];

{x,\[Gamma],f}=
{x,\[Gamma],f}/.FindRoot[{1-vG/((1-v\[Tau])*(vP
*x-vc*vP*x))==\[Gamma],vb
*\[Gamma]
*(1-v\[Tau])
*(vP-vc*vP)*
(\[Gamma]*(1-v\[Tau])*(vP*x-vc*vP
*x))^(-2)==f
*vmu*Exp[(vxbar-vmu
*x-v\[Sigma]^2/2)/10000],1-Exp[(vxbar-vmu

```

```
*x-v\[Sigma]^2/2)/10000]-vmu*x/(vmu*f)==-f*Exp[(vxbar-vmu*x-v\[Sigma]
^2/2)/10000]*vmu*x/(vmu*f)},{x,30000},{\[Gamma],0.5},{f,40}}];
```

```
bbar=vb*1.2;
```

```
{xs,\[Gamma]s}=          {xs,\[Gamma]s}/.FindRoot[{1-vG/((1-v\[Tau])*(vP
*xs-vc*vP  *xs))}==\[Gamma]s,bbar*\[Gamma]s *(1-v\[Tau]) *(vP-vc*vP)*
(\[Gamma]s*(1-v\[Tau])*(vP*xs-vc*vP*xs))^(-2)+vP-vc*vP==amen},{\[Ga
mma]s,0.1},{xs,50000}}];
```

```
cswl=bbar*(1/(\[Gamma]*(1-v\[Tau])*(vP*x-vc*vP*x))-1/(\[Gamma]s*(1-v\[
Tau])*(vP*xs-vc*vP  *xs)))+vP*xs-vc*vP  *xs-(vP*x-vc*vP
*x)+amen*(vmu*x-xs)+2.8;
```

```
Return[cswl]]
```

```
swl=swlcompute /@ data;
```

```
TableForm[swl]
```

```

Psenstiveanalysis[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_}]:=Module[
{vG,v\[Tau],vP,vb,vxbar,v\[Sigma],vc,vmu},
vG=G;
v\[Tau]=\[Tau];
vP=P;
vb=b;
vxbar=xbar;
v\[Sigma]=\[Sigma];
vc=c;
vmu=mu;
d=Range[5];

d[[1]]=swlcompute[{vG,vP*0.8,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[2]]=swlcompute[{vG,vP*0.9,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[3]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[4]]=swlcompute[{vG,vP*1.1,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[5]]=swlcompute[{vG,vP*1.2,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];

Return[d]]

```

```

Panalysis=Psenstiveanalysis/@ data;

TableForm[Panalysis]

Export["C:\\Users\\lenovo\\Desktop\\Panalysis.xlsx",Panalysis]

Gsenstiveanalysis[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_}]:=Module[
{vG,v\[Tau],vP,vb,vxbar,v\[Sigma],vc,vmu},

vG=G;

v\[Tau]=\[Tau];

vP=P;

vb=b;

vxbar=xbar;

v\[Sigma]=\[Sigma];

vc=c;

vmu=mu;

d=Range[5];

d[[1]]=swlcompute[{vG*0.8,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[2]]=swlcompute[{vG*0.9,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[3]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[4]]=swlcompute[{vG*1.1,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];

```

```

d[[5]]=swlcompute[{vG*1.2,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];

Return[d]]

Ganalysis=Gsenstiveanalysis/@ data;

TableForm[Ganalysis]

Export["C:\\Users\\lenovo\\Desktop\\Ganalysis.xlsx",Ganalysis]

bsenstiveanalysis[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_}]:=Module[

{vG,v\[Tau],vP,vb,vxbar,v\[Sigma],vc,vmu},

vG=G;

v\[Tau]=\[Tau];

vP=P;

vb=b;

vxbar=xbar;

v\[Sigma]=\[Sigma];

vc=c;

vmu=mu;

d=Range[5];

```

```

d[[1]]=swlcompute[{vG,vP,vb*0.8,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[2]]=swlcompute[{vG,vP,vb*0.9,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[3]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[4]]=swlcompute[{vG,vP,vb*1.1,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[5]]=swlcompute[{vG,vP,vb*1.2,v\[Sigma],v\[Tau],vxbar,vc,vmu}];

Return[d]]

banalysis = bsenstiveanalysis /@ data;

TableForm[banalysis]

Export["C:\\Users\\lenovo\\Desktop\\banalysis.xlsx", banalysis]

sigmasensitiveanalysis[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_}]:=Module[{vG,v\[Tau],vP,vb,vxbar,v\[Sigma],vc,vmu},
vG=G;
v\[Tau]=\[Tau];
vP=P;
vb=b;
vxbar=xbar;

```



```

v\[Sigma]=\[Sigma];

vc=c;

vmu=mu;

d=Range[5];

d[[1]]=swlcompute[{vG,vP,vb,v\[Sigma]*0.8,v\[Tau],vxbar,vc,vmu}];
d[[2]]=swlcompute[{vG,vP,vb,v\[Sigma]*0.9,v\[Tau],vxbar,vc,vmu}];
d[[3]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[4]]=swlcompute[{vG,vP,vb,v\[Sigma]*1.1,v\[Tau],vxbar,vc,vmu}];
d[[5]]=swlcompute[{vG,vP,vb,v\[Sigma]*1.2,v\[Tau],vxbar,vc,vmu}];

Return[d]]

sigmaanalysis=sigmasensitiveanalysis/@ data;

TableForm[sigmaanalysis]

Export["C:\\Users\\lenovo\\Desktop\\sigmaanalysis.xlsx",sigmaanalysis]

tausensitiveanalysis[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_}]:=Modul

```

```

e[{vG,v\[Tau],vP,vb,vxbar,v\[Sigma],vc,vmu},

vG=G;

v\[Tau]=\[Tau];

vP=P;

vb=b;

vxbar=xbar;

v\[Sigma]=\[Sigma];

vc=c;

vmu=mu;

d=Range[5];

d[[1]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau]*0.8,vxbar,vc,vmu}];
d[[2]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau]*0.9,vxbar,vc,vmu}];
d[[3]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[4]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau]*1.1,vxbar,vc,vmu}];
d[[5]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau]*1.2,vxbar,vc,vmu}];

Return[d]]

```

```

tauanalysis=tausenstiveanalysis/@ data;

TableForm[tauanalysis]

Export["C:\\Users\\lenovo\\Desktop\\tauanalysis.xlsx",tauanalysis]

xbarsensitiveanalysis[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_}]:=Modu
le[{vG,v\[Tau],vP,vb,vxbar,v\[Sigma],vc,vmu},

vG=G;

v\[Tau]=\[Tau];

vP=P;

vb=b;

vxbar=xbar;

v\[Sigma]=\[Sigma];

vc=c;

vmu=mu;

d=Range[5];

d[[1]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar*0.8,vc,vmu}];

d[[2]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar*0.9,vc,vmu}];

d[[3]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];

d[[4]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar*1.1,vc,vmu}];

```

```

d[[5]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar*1.2,vc,vmu}];

Return[d]]

xbaranalysis=xbarsensitiveanalysis/@ data;

TableForm[xbaranalysis]

Export["C:\\Users\\lenovo\\Desktop\\xbaranalysis.xlsx",xbaranalysis]

csensitiveanalysis[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_}]:=Module[{
vG,v\[Tau],vP,vb,vxbar,v\[Sigma],vc,vmu},vG=G;

v\[Tau]=\[Tau];

vP=P;

vb=b;

vxbar=xbar;

v\[Sigma]=\[Sigma];

vc=c;

vmu=mu;

d=Range[5];

d[[1]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc*0.8,vmu}];

```

```

d[[2]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc*0.9,vmu}];
d[[3]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];
d[[4]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc*1.1,vmu}];
d[[5]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc*1.2,vmu}];

Return[d]

```

```

canalysis=csestiveanalysis/@data;

```

```

TableForm[canalysis]

```

```

Export["C:\\Users\\lenovo\\Desktop\\canalysis.xlsx",canalysis]

```

```

musestiveanalysis[{G_,P_,b_,\[Sigma]_,\[Tau]_,xbar_,c_,mu_}]:=Modul

```

```

e[{vG,v\[Tau],vP,vb,vxbar,v\[Sigma],vc,vmu},vG=G;

```

```

v\[Tau]=\[Tau];

```

```

vP=P;

```

```

vb=b;

```

```

vxbar=xbar;

```

```

v\[Sigma]=\[Sigma];

```

```

vc=c;

```

```

vmu=mu;

```

```

d=Range[5];

```

```
d[[1]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu*0.8}];  
d[[2]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu*0.9}];  
d[[3]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu}];  
d[[4]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu*1.1}];  
d[[5]]=swlcompute[{vG,vP,vb,v\[Sigma],v\[Tau],vxbar,vc,vmu*1.2}];  
  
Return[d]  
  
muanalysis=musenstiveanalysis/@data;  
  
TableForm[muanalysis]  
  
Export["C:\\Users\\lenovo\\Desktop\\muanalysis.xlsx",muanalysis]
```