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Essays on Social Institutions and Economics

Fusako Tsuchimoto Menkyna

Dissertation

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To Júlia Sakura and Robert

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Abstract

This thesis investigates how the economy and social institutions affect each other. Specifically, the first chapter analyzes the interaction between politics and the economy: how the political parties form a coalition in the government to implement their preferred fiscal policy. The second chapter examines the effect of criminal law reform on the behavior of agents in the court process in the United States, applying econometric methodology. The last chapter statistically reports on the change in the emissions of local air pollutants in the Czech Republic, reflecting the new requirement of EU regulations and economic growth during the transition period.

The first paper examines how the two dimensions of heterogeneity of people in society, income disparity and ethnic diversity, affect the government formation and eventually the reallocation of income. A legislative bargaining model is constructed to investigate how political parties, whose platforms are distinguished by the ethnicity and income group they belong, form a coalition and enter a government. The result of the model, where the agenda setter gives the minimum to the partner, suggests that the preferred partner in a coalition is the group with the smaller population size (cheaper to buy) and lower income level (easier to tax), which are quite intuitive results, considering the minimal(minimum)-winning coalition theory. Further the model is extended from a one-round to a two-round game. In fact, the extended model shows that forming an oversized coalition might be the optimal strategy, which is consistent with the empirical findings in some developed countries such as Denmark or Sweden.

The second paper analyzes the effect of criminal law reform on the behavior of agents during litigation and is coauthored with Libor Dusek. We investigate behavioral responses of judges and prosecutors to more severe punishments by analyzing the effects of Truth-in-Sentencing (TIS) laws in a large sample of individual criminal cases in the United States. The TIS laws raised effective punishment by requiring offenders to serve at least 85% of their imposed sentence in prison. Differences between the states in the timing of adoption and the types of crimes covered provide a source of identification. The key findings are: (1) The TIS laws reduced the probability that an arrested offender is eventually convicted by 8% through an increase in the probability that the case is dismissed, a reduction in the probability that the defendant pleads guilty, and a reduction in the probability that the defendant is convicted at trial. (2) The TIS laws reduced the imposed sentence that a defendant may expect upon arrest by 2%. The behavioral responses are empirically important to partially mitigate the intended deterrent effect of the TIS laws.

The third paper statistically documents how the relationship between economy and environmental degradation changes under the regulation and is coauthored with Milan Scasny. We statistically decompose the change in the emission level of the various air pollutants such as SOx, CO, NOx, VOC and particulate matters (PM) in the Czech Republic. First, we decompose the emission level in 1995-2007 into three factors: the emission intensity effect, the scale effect, and the composition effect. We find that the implementation of command and control type laws which require large sources of emissions to satisfy emission limits till 1999, highly correlates with a reduction in the emission levels of SOx, NOx, CO, and PM. Moreover, the reduction was mainly induced by a change in the emission intensity effect, which captures the environmental efficiency relative to the per capita GDP. We further decompose emission intensity effect into three factors for a more refined analysis: (1) fuel intensity effect (2) fuel mix effect, and (3) emission coefficient effect. We find that the emission coefficient effect is the most prominent factor, especially during the period of 1995-1999. In other words, command and control regulation motivates firms to decrease their emission levels by improving abatement technology, which reduces the emission amount given the same amount of fuel.

Tato práce zkoumá, jak se vzájemně ovlivňují ekonomika a sociální instituce.

První kapitola zkoumá, jak dvě dimenze rozdílnosti lidí ve společnosti, příjmová nesourodost a etnická rozmanitost, ovlivňují formování vlády a nakonec přerozdělení příjmů. Model legislativního vyjednávání je postaven tak, aby zkoumal, jak politické strany, jejichž platformy jsou rozpoznatelné podle etnické a příjmové skupiny, do kterých patří, vytvoří koalici a vstoupí do vlády. Výsledky modelu, kde tvůrce vládní agendy dává minimum partnerovi, naznačuje, že preferovaným partnerem v koalici je skupina s menším počtem obyvatel (dá se zavázat levněji) a nižší úrovní příjmů (jednodušší danění). To jsou vcelku intuitivní výsledky, vzhledem k teorii minimální vítězné koalice. Dále je model rozšířen z jednokolové na dvoukolovou hru. Rozšířený model ukazuje, že tvoření příliš velké koalice může být optimální strategie, což je v souladu s empirickými poznatky v některých vyspělých zemích jako je Dánsko nebo Švédsko.

Druhý článek analyzuje vliv reformy trestního práva na chování agentů během soudních sporů, a jeho spoluautorem je Libor Dušek. Zkoumáme reakce v chování soudců a státních zástupců na zpřísnění trestů na základě analýzy dopadů Truth-in-Sentencing (TIS) zákonů na velkém vzorku trestních případů ve Spojených státech. TIS zákony zvýšily efektivní tresty tím, že pachatelům ukládají odpykat si nejméně 85 procent z vyměřené délky trestu ve vězení. Jako zdroj identifikace slouží rozdíly mezi státy v načasování přijetí a vztahujících se druzích trestné činnosti. Mezi hlavní zjištění patří: (1) TIS zákony snižují pravděpodobnost, že zatčený pachatel je nakonec odsouzen o 8% v důsledku zvýšení pravděpodobnosti, že případ bude zamítnut, snížení pravděpodobnosti, že obžalovaný se přizná, a snížení pravděpodobnosti, že obžalovaný bude odsouzen u soudu. (2) TIS zákony snižují uložený trest, který obžalovaný může po zatčení očekávat, o 2%. Tyto změny v chování jsou empiricky důležité k zmírnění zamýšlených odrazujících účinků TIS zákonů.

Třetí článek, jehož spoluautorem je Milan Ščasný, statisticky dokumentuje, jak se mění vztah mezi ekonomikou a znečišťováním životního prostředí v rámci změn regulace. Statisticky jsme rozložili změny v úrovni emisí jednotlivých znečišťujících látek v ovzduší, jako jsou SOx, CO, NOx, VOC a prachových částic (PM), v české republice. Zjistili jsme, že implementace zákonů typu směrnic a nařízení, které požadovaly po velkých zdrojích znečistění dodržení emisních limitů do roku 1999, silně souvisí se snížením úrovní emisí SOx, NOx, CO a PM. Navíc regulace typu směrnic a nařízení motivuje firmy snížit jejich úrovně emisí zlepšením technologie snižování emisí, které snižuje emise při zachování stejného množství paliva.

Chapter 1

A Theory of Ethnic Diversity and Income Distribution: The Legislative Bargaining Approach

Fusako Tsuchimoto Menkyna

Abstract

This paper examines how the two dimensions of income disparity and ethnic diversity affect political coalition formation and the reallocation of income. I construct a legislative bargaining model to investigate along which dimension a political coalition is formed. The results of the model suggest that the partner for a coalition is the group with a lower aggregate income: a smaller population size and a lower income level. Further, I extend the model from a one-round to a two-round game. The extended model shows that forming an oversized coalition is a possible political outcome, as opposed to the theory of the minimum winning coalition, but more consistent with empirical findings.

Keywords: Political economy; Diversity; Legislative bargaining; Oversized coalition

JEL Codes: D3; D7; H3; H4

1.1 Introduction

Ethnic diversity has been considered to have a negative impact on an economy because the diversity of people tends to lead to a political conflict, fighting for particular interests. In this regard, Alesina and Glaser (2004), however, argue that ethnic diversity is not necessarily equivalent to ethnic conflict: The negative effect of diversity does not appear if the ethnic minority are rich. However, their argument does not quite hold in the case of Rwanda, where the ethnic minority Tutsi are also relatively rich, but they still fight for redistribution. Here lies the starting point of this paper: If the ethnic minority are rich, does it always decrease the ethnic political conflict?

This paper partially answers this question by analyzing political coalition formations along two dimensions: income inequality and ethnic diversity. Specifically, I analyze under what circumstances the political coalitions along ethnic lines and income class are formed using a simple legislative bargaining model. There is a gap in the literature: It is assumed that ethnic diversity leads to ethnic political conflict. Further, there are very few studies which study the effect of diversity when the diversity is multi-dimensional. This paper tries to fill this gap by analyzing the political coalition formation when there are the two dimensions of income disparity and ethnic diversity and examines under which conditions the ethnic diversity leads to ethnic political coalitions.

In this respect, Przeworski (2005) claims that the relative size of an ethnic group does not necessarily correlate with the share of the vote of the ethnic political group i.e., the population size of an ethnic group does not have to coincide with that of political parties representing ethnic groups, which suggests that the political outcome does not always reflect the ethnic diversity in the population.[1] Below is a modified example from Przeworski. Assume that everybody can stand as a candidate as in the citizen-candidate model.[2] There are two ethnic groups, A and B, and additionally within the group, some of the members are rich and some are poor. Thus, we can classify people into four groups: A and rich, B and rich, A and poor, and B and poor. Assume that each group has a population size smaller than one-half, and thus to get a majority of agreement, each group has to make a coalition with another. They can form a coalition either along ethnic lines or according to their income class. Because they divide a fixed pie within the coalition

[1] In this regard, Posner (2005) also argues that people usually have several attributes such as linguistic, income level or ethnicity, along which they vote.

[2] For details of the citizen-candidate model, see Osborne and Slivinski (1996) as the pioneer work or Coate and Besley (1997), who point out the tractability of the model under a mutli-dimensional policy space.

if they win, they want to form a coalition which is a majority but as small a population size as possible. Let's consider two cases which are presented in the table below.

	rich	poor	total
A	*25*	35	60
B	*30*	10	40
total	*55*	45	100

	rich	poor	total
A	*10*	*45*	*55*
B	30	15	45
total	40	60	100

The numbers in each cell express the population of each group respectively. In both tables, the ethnic minority B are relatively rich (the proportion of the rich is larger than the poor). In the left table above, the group of the rich forms a coalition because the population size of the coalition of the income class group, the rich (55%), is smaller than that of the ethnic majority group A (60%).[3] On the other hand, in the right table, the ethnic group A can win with a smaller portion of votes (55%) than the coalition of the income class group, the poor (60%); thus, group A would form a coalition as in the case of Rwanda. In both cases, the ethnic minority B are relatively rich; however, the political result is different. Political ethnic conflict is more likely to occur in the case of the right table, where the coalition is formed along ethnicity.

Although this paper is based on quite a similar idea to Przeworski's (2005), there are two main points where this paper is significantly different from his. First, Przeworski's example mainly deals with the voting; however, in this paper, government formation in the legislature, i.e., one stage after voting, is considered.[4] Secondly, in Przeworski, only the population size of the group is considered, whereas in this paper, income distribution is also taken into account. In fact, the introduction of income difference to the ethnic diversity of people leads to interesting findings: The coalition is likely to be formed with the group whose population size is smaller, and the income level is relatively low because its outside option when it is outside of the coalition is low, and thus, it is cheaper to subsidize that group to be a partner in a coalition. This finding might provide a key insight into the question why we see ethnic-based coalitions in most of the countries in Africa, where each ethnic group is small in population size, and the income level is low. In Table 1.1, I summarize the coalition type across world regions in the year 1975-2006.

[3]Alternatively, if the poor are in the majority and have a smaller population size than the ethnic majority group, the poor forms a coalition and enters the government.

[4]Regarding the analysis of the voting stage, for example, Wrede (2009) analyzes the redistribution when there is inter- and intra-regional diversity within the state, using the citizen-candidate model.

Here, a "non-economic coalition" is defined as either (1) within a political coalition in the government, where the right and left wing parties co-exist or (2) the largest party in the government is neither left nor right wing. As you can see in Africa, compared to other regions, the share of non-economic coalitions over all the types of coalitions is much higher, which is consistent with the findings of this paper.

Another theoretical finding of this paper is that when the poor are in the majority, and the income difference between the rich and the poor is above the threshold, political coalitions along class lines are formed. In fact, this finding partially explains the political situation in Latin America, where the income inequality is very high as can be seen in Table 1.3, and coalitions based on class are more likely to be formed. When the rich are in the majority, this relation between income difference and coalition formation gets reversed: If income inequality is above the threshold, ethnic coalitions are likely to be formed. If we consider the stylized fact that income inequality is relatively high when countries are poor and when they become richer, income inequality tend to decrease,[5] coalitions along ethnicity are formed only in poor countries but not in the middle-income and rich countries. This might give some insights into why we tend to see ethnic coalition in developing countries, but not often in developed countries, as you can see in Table 1.1.

The results above are when bargaining occurs only in one round and is consistent with Riker's (1962) minimal winning coalition theory and many others: A coalition will form with as small a group as possible as long as it is winning. However, in the reality, this is not all the time case. In fact, as in Volden and Carruba (2004), almost half of the coalitions are oversized rather than minimal winning. Here, an oversized coalition is defined as "any coalition in which at least one party can be removed with the remaining members still controlling a majority of seats" (Volden and Carruba 2004, pp.526). In Table 1.2, I summarize the share of the oversized coalition over all the types of coalitions across the different regions.[6] In fact, in some regions, more than half of the coalitions are oversized. To explain the mechanism of oversized coalitions, I extend the model from a one-round to a two-round bargaining game. When the game has two rounds, the agenda setter chooses the group with the larger population size and higher income with which to form a coalition. This is because the group with the larger population size and higher income has a lower expected utility when the game proceeds to second round, and thus,

[5]Kuznets (1955) shows that income inequality increases when countries are in transition from low- to middle-income. Afterwards, when countries become more economically developed, income inequalities tend to decrease.

[6]The number is the average share of countries in the regions.

its reservation utility is lower in the first round. In turn, it is easier for the agenda setter to make an offer to the group with a lower reservation utility. This finding is a new explanation in the field for oversized coalitions, which is another contribution of this paper.

Most theoretical studies predict minimal winning coalitions, but there are some which predict oversized coalitions similar to this paper. Baron and Diermeier (2001) and Diermier and Merlo (2000) explain that the agenda setter chooses to form a coalition with a larger population size to extract more rent within the coalitions. On the other hand, Bandyopadhyay and Oak (2008) show that oversized coalitions occur when the agenda setter needs to "balance" the policy implemented: Both parties which are on the opposite ideological ends have to be invited together to set the policy around the point where the agenda setter prefers. In this regard, this paper tries to give a new viewpoint on oversized coalitions vis-à-vis the reservation utilities of the partner groups.

There are several empirical studies that report a negative relationship between ethnic or religious diversity and economic development. The leading papers are by Easterly and Levine (1997), Alesina, Baqir, and Easterly (1999) and Alesina, Devleeschauwer, Easterly, Kurlat, and Wacziarg (2003). Alesina et al. (2003) extend the measurement of diversity in society by adding linguistic and religious diversity. Further, Keely and Tan (2008) empirically show, using the General Social Survey data, that people believe that the redistribution should be based on race, sex and income class background in the United States. Their results strongly encourage a theoretical analysis, where the political parties differ in multi-dimensions.[7]

There are only a few theoretical studies regarding ethnic diversity. In terms of the question on how the diversity of people affects economic development, there are two major theoretical approaches. The first approach introduces the externalities that arise from the diversity of people and examines how these externalities affect the welfare of society or economic growth.[8] The second approach analyzes a political game among parties to implement their preferred policy, as in this paper.

One of the studies categorized in the second approach, Fernandez and Levy (2008), investigate political equilibrium with diversity in the population and argue that there would be less redistribution to the poor with a higher degree of diversity. There are some

[7]In this respect, Roemer (2004) theoretically analyzes political equilibrium with multi-dimensional preferences. This paper is more specific and elaborates on the stage of government formation.

[8]For example, Esteban and Ray (1999) introduce externalities and analyze the links between the level and pattern of conflict and the distribution of the groups of people with specific interests.

limitations in their model. First, their result of a non-monotonic relation between diversity and redistribution depends crucially upon the assumption that there is an exogenous fixed cost to the provision of public goods. Secondly, they assume that rich people are united, and only the poor people are diversified. In my model, the rich are diversified, and whether the rich unite or not is endogeneized in the political process of coalition formation.

Similarly Azzimonti-Renzo (2006) analyzes how a government policy results in an inefficient allocation when there are two opposing political groups which have a conflict over the redistribution allocation, using a recursive formulation with probabilistic voting. She succeeds in showing the negative relationship between ideological diversity in society and economic growth, assuming that people vote along their ethnic attributes. In other words, once the party is chosen in an election, the promised platform is implemented (direct democracy). This paper analyzes the stage after voting, i.e., political coalition formation in the legislature.

In the following sections, first the model and its finding are presented. Secondly, the extended model, which overcomes the shortcomings of the basic model, is presented. Finally, the discussion and conclusion follow.

1.2 Model

1.2.1 Environment

Let us consider a society with two distinct ethnic groups (A and B), e.g., *Amber* and *Blue* and two income groups, *Rich* and *Poor* within each ethnic group A and B i.e., there are 4 distinct groups, A and *Rich* (AR), A and *Poor* (AP), B and *Rich* (BR), and B and *Poor* (BP). Group $h \in \{AR, AP, BR, BP\}$ has a population size $n(h)$, and within each group, people are assumed to have the same level of per-capita income $Y(h)$. To analyze the coalition formation, I assume that each group cannot be the majority alone: $0 < n(h) < 0.5,\ \forall h$. For simplification, the population size of the society and total income of society Y are normalized to one ($\sum_h n(h) = 1; Y = \sum_h n(h)Y(h) = 1$).[9]

Additionally for simplicity, it is assumed that there is no per-capita income difference among the groups in the same class:

[9]Thus, $Y(h)$ expresses how the income level of group h differs from the average income of society, Y.

Assumption 1

$$Y(AR) = Y(BR) = Y(R);\; Y(AP) = Y(BP) = Y(P).$$

In the environment described above, a one-round legislative bargaining model is constructed following Diermeier and Merlo (2000) or Baron and Diermeier (2001). To implement the preferred policy, the group has to make a coalition with another group to win a majority in government. Let's call the coalition which enters the government and implements their preferred policy as the *winning coalition*.[10] The winning coalition implements its preferred policy if it is formed, $T(i,j) = \{t(i,j),\ \tau(h|i,j)\}$, for all h. Namely $T(i,j)$ consists of a common tax rate and transfers along the lines of income class, ethnicity or both.

The sequence of legislative bargaining is as follows:

(S1) The agenda setter i chooses a partner group j and makes a policy proposal $T(i,j)$.[11]

(S2) Partner j decides if he accepts an offer or not. If he accepts, the game ends, and a winning coalition is formed with i and j, and $T(i,j)$ would be implemented. If not, the game proceeds to (S3).

(S3) If a coalition is not formed, no government is formed, the default policy $T(q)$ will be implemented.

Assumption 2 *The agenda setter i satisfies the following condition:*

$$n(i) + n(\widetilde{j}) > 0.5 \textit{ and } n(i) + n(\widehat{j}) > 0.5, \tag{1.1}$$

where $\widetilde{j}$ denotes the group which has the same ethnicity as group i, and $\widehat{j}$ denotes the group which has the same income level as i.

For example, $\widetilde{j} = AR$ if $i = AP$, and $\widehat{j} = AR$ if $i = BR$. Note that the group which would be selected as an agenda setter has to belong to the majority group in both lines, ethnicity and income class; however, it does not have to have a large population size itself. Interestingly, it can occur that the group with a small population size can be an agenda setter and thus have strong bargaining power just because it can choose its partner. For example, even if the population share of group AP is just, say, 5% when A is the majority

[10]The concept of a winning coalition has been often used in the literature: see Mesquita, Smith, Siverson, and Morrow (2005), for example.

[11]In the literature, the agenda setter group i is chosen according to recognition probabilities, which are the probabilities of each group being chosen as an agenda setter.

and P is the majority, then group AP would be the agenda setter. Thus, it has strong bargaining power and will be in the winning coalition all the time if one is formed. This assumption is made to focus on which partner will be chosen if there is any choice.

Assumption 3 *Under the default policy, no tax would be collected, and thus, no redistribution occurs:*

$$T(q) = \{t(i,j) = 0, \tau(h|i,j) = 0\}, \text{ for all } h.$$

With assumption 3, the reservation utility of the partner group j under the default policy would be:

$$\overline{u}(h) = Y(h). \tag{1.2}$$

For the tractability of the model, the possibility of a consensus government is excluded.[12]

The budget constraint of the government is:

$$\sum_h n(h)\tau(h\ |i,j) = Y \cdot \left(t(i,j) - \frac{t(i,j)^2}{2} \right), \tag{1.3}$$

where $t(i,j)$ is the tax rate that depends on which group is a policy proposer and partner, $\frac{t(i,j)^2}{2}Y$ is the associated cost of collecting and reallocating the tax[13] following the specification of Bolton and Roland (1997), and $n(h)\tau(h|i,j)$ denotes the transfer to group h.

The preference of the member in group h is described by the following utility function:

$$u(h|i,j) = (1 - t(i,j)) \cdot Y(h) + \tau(h|i,j), \tag{1.4}$$

where $t(i,j)$ is the common flat tax rate on income, which is the same for everybody in the society, and $\tau(h|i,j)$ denotes a per-capita transfer to the member group h, which is group specific. It can be easily seen that the agenda setter, in this case, has no incentives to provide transfers outside of the coalitions, i.e., the positive transfer is provided only to the agenda setter and partner group. Thus, I can specify the per capita transfer in the

[12] By a consensus government, I mean a 3-group coalition which excludes the agenda setter to prevent the formation of a winning coalition. If I include the possibility of a consensus government, the choice of partner j would be either to form a coalition with the agenda setter or to be in a consensus government. However, for further research, admittedly, considering this alternative would make this analysis richer.

[13] Here the cost of redistribution is defined as a convex function of tax. Of course, one can generalize the cost c = g(t). However, the convexity of the cost function is assumed to have an interior solution because the analysis of a corner solution case is not the main objective of this paper.

following way:

$$\tau(i|i,j) = \frac{(1-\alpha(i,j))(t(i,j) - \frac{t^2(i,j)}{2}) \cdot Y}{n(i)},$$

and

$$\tau(j|i,j) = \frac{\alpha(i,j)(t(i,j) - \frac{t^2(i,j)}{2}) \cdot Y}{n(j)}.$$

Basically, the collected tax minus deadweight loss is divided among the agenda setter and the partner group, and the proportion of $\alpha(i,j)$ is given to the partner group, and the rest is taken by the agenda setter group.

Now in the parliament, each political group tries to implement their own preferred policy, i.e., the policy which maximizes the sum of the utility of the members of its own group.

The agenda setter i chooses a tax rate, a group-specific transfer or an allocation of the collected tax between the agenda setter and the partner group invited to form a coalition, maximizing the utilities of the members in group i:

$$\begin{aligned}
\underset{t,\alpha,j}{max}\ u(i|i,j) &= (1-t(i,j))Y(i) + \tau(i|i,j) && (1.5)\\
s.t. u(i|i,j) &\geq \overline{u}(i) && (1.6)\\
u(j|i,j) &\geq \overline{u}(j) && (1.7)\\
t(i,j) &\geq 0 && (1.8)\\
\tau(i|i,j) &= \frac{(1-\alpha(i,j))(t(i,j) - \frac{t^2(i,j)}{2}) \cdot Y}{n(i)} && (1.9)\\
0 &\leq \alpha(i,j) \leq 1. && (1.10)
\end{aligned}$$

The first constraint is for the agenda setter to start the game, i.e., his incentive compatibility constraint. The second constraint is for the partner to accept the offer: The partner gets more than his reservation utility ($\overline{u}(j)$) if he accepts the offer. Further, the tax rate is assumed to be non-negative, and the share of the pie which the partner gets is assumed to be in the range of 0 to 1 such that both the partner and the ageda setter get a positive lump-sum transfer. As mentioned above, $\tau(i|i,j)$ can be expressed as the part of the net collected tax, which the agenda setter gets divided among the members of the agenda setter group. To solve the equilibrium outcome easily, when the agenda setter is indifferent between forming a coalition or does not make an offer and accepts the status quo, I assume that he forms a coalition. The same logic applies to the second inequality: If the partner is indifferent between accepting the offer and rejecting the offer, he accepts.

Note that the agenda setter of course can choose the default policy if it is more beneficial for him rather than form a coalition. Note that when the third constraint, $t(i,j) \geq 0$ and $u(i|i,j) \geq Y(i)$, are satisfied, the constraint of $\alpha \leq 1$ is satisfied all the time and thus, redundant.[14]

1.2.2 The Definition of Equilibrium

Given the population sizes and the income level of each group, $n(h)$ and $Y(h)$ for all h, an equilibrium is an equilibrium coalition $\{i^*, j^*\}$, the equilibrium policy $T(i^*, j^*)$ and the utilities of members in each group, $u(h|i^*, j^*)$, $\forall h$, such that

(a) i^* satisfies (1.1);

(b) $\overline{u}(j)$ is given by (1.2); and

(c) j^* & $T(i^*, j^*)$ solves (1.5)-(1.10).

1.2.3 The Characterization of Equilibrium

We can assume that ethnic group A is the majority in the society without loss of a generality:

$$n(AR) + n(AP) > 0.5.$$

Assumption 4 *The agenda setter never forms a coalition with a group with two different attributes.*

This assumption is made to focus on answering the question, "which type of coalition occurs, ethnicity or income class?" If other groups are chosen as an agenda setter, then the group belongs to the majority in either way, they have only one or no choice for a possible partner with which to form a winning coalition: For example, if A and the Rich are in the majority and AP is chosen as an agenda setter, he has only one choice to form a coalition with AR to win the majority because forming a coalition with BP would not win the majority. That is why I focus on the case where the agenda setter is the group which is in the majority either by ethnicity or income class. [15]After this assumption is made, the following proposition can be derived.

Proposition 1. *The agenda setter prefers to form a coalition with the partner who has a lower aggregate income* $(n(j)Y(j))$.

[14]If we assume that $t(i,j) \geq 0$ and $\alpha > 1$, then $u(i|i,j) < Y(i)$, which is a contradiction. Thus, $\alpha \leq 1$.

[15]partner, the principle how he would choose the partner is robust: He choses the group with the smaller population size and lower income level.

Proof. See Appendix □

The agenda setter basically chooses a partner who has a lower income and whose population size is smaller so that it is cheaper to persuade him to be a partner in a winning coalition, because his reservation utility under the default policy is lower than the group with the higher income and larger population size. In other words, considering that the agenda setter has to give some proportion, it is easy to agree with the group that has a lower aggregate income with higher taxation.

The Ethno-linguistic Index (ELF index), constructed by Alesina et al. (2003), measures the probability of two randomly selected individuals coming from different ethnic or linguistic groups. It suggests that most countries in Africa have a higher value in this index compared to other parts of the world. In other words, if there is a large number of different ethnic groups, this index would be higher as in the case of Africa. A large number of ethnic groups means that the population size of each ethnic group tends to be small. Thus basically, this proposition suggests that in the countries with a higher ELF index, an ethnic coalition is more likely to be formed because the aggregate income of each ethnic group is small, which is consistent with most countries in Africa. For example, in Kenya, whose ELF index is one of the highest, the largest ethnic group shares only 22% of the total population, and the other 6 ethnic groups share only a little more than 5% each. In fact, Miguel and Gugerty (2004) report on how ethnic conflict and diversity lead to lower public goods provision in Kenya such as school attainment or water access.[16]From this proposition, the following corollary can be derived.

Corollary 1. *If the poor are in the majority, and the income difference is sufficiently large, a class coalition is likely to be formed. In contrast, if the rich are the majority, and the income difference is sufficiently large, an ethnic coalition is likely to be formed.*

Proof. See Appendix. □

The first statement of the corollary answers why we see a class coalition in Latin American countries where inequality is high, as you can see in Table 1.3, where the summary statistics of the gini across regions are presented.[17] Thus, this corollary partly

[16]Their results suggest that when the ethnically based coalition enters government, it leads to a policy oriented, specific ethnic groups, and thus, it leads to a lower provision of constructive public goods.

[17]Admittedly the income difference between rich and poor captures only one perspective of the Gini coefficient. It is rather close to the other measurement of inequality, e.g., the income ratio of the top 20% rich and the bottom 20%, which is also used in the Human Development Report by the UNDP.

explains why we see income class conflict in Latin America rather than ethnic conflict (white vs. mestizo vs. indigenous) as Fearon (2005) argues.

On the other hand, the second part of the corollary says that when the rich is the majority, this relationship between income level difference and the preferred partner would be reversed, i.e., as income difference becomes larger, the ethnic partner is preferred. In other words, the relationship between income level difference and coalition formation is not monotonic. The Kuznets (1955) curve suggests that income inequality and the level of GDP per capita of the countries should have an inverse-U relationship.

In this regard, Horowitz (1985) argues that in most countries in South Asia, where income inequality is not so high, we see that ethnically based parties are formed, and they are usually too strongly rooted in their own ethnicity to make a coalition across ethnicities, which fits more to the first part of corollary, i.e., when the poor are in the majority. Of course, there are some exceptions such as the multi-ethnic coalition in Sri Lanka as Horowitz discusses in his book. However, usually these coalitions are unstable and momentary.

So far, I have analyzed the case where income difference is introduced within ethnic groups using a legislative bargaining model. It certainly gives a richer analysis compared to the model with only one dimension of heterogeneity; however, it suggests that *ceteris paribus* the coalitions with smaller population sizes are preferred. However in reality, it is not always true: We often see an oversized coalition. To overcome these shortcomings, I extend the basic legislative bargaining model such that there are two rounds of bargaining instead of one round.

1.2.4 The Characterization of Equilibrium — Extended Model

In this section, I show a model with two-round legislative bargaining. Basically if the agenda setter is rejected in the first round, he could go to another possible partner and make the offer to form a coalition. The sequence of the game in this case is the following:

Sequence of the game

(S1) The agenda setter i is determined and decides whether to start the game or not: The agenda setter is the group who belongs to the majority along either line, ethnicity or income class.

(S2) The agenda setter chooses the partner j_1 with whom to form a coalition and makes the offer $T_1(i, j_1) = \{t_1(i, j_1),\ \tau_1(h|i, j_1)\}$, for all h, where t is the tax rate, and

τ_1 is the group specific per capita transfer in the first round.

(S3) If j_1 accepts, the winning coalition is formed and it enters the government to implement their preferred policy T_1.

(S4) If j_1 rejects, the agenda setter chooses another partner with whom to form a coalition j_2 and makes the offer $T_2(i, j_2) = \{t_2(i, j_2),\ \tau_2(h|i, j_2)\}$, for all h,

(S5) If j_2 accepts, the winning coalition is formed, and implements their preferred policy, T_2.

(S6) If j_2 rejects, no government is formed, and the status quo q is implemented.

Note that the lower subscript of the variables expresses the order of the round of the game. The maximization problem of the agenda setter is as expressed in (4). The only difference between the first round and second round is the outside option of the partner and the agenda setter, i.e., the reservation utilities, $\overline{u}(j)$ and $\overline{u}(i)$, differ. In the second round, the agenda setter offers a partner such that the partner is as well off as his outside option–status quo policy. On the other hand, in the first round, the rservation utility of the partner is the value funciton when he is outside of the winning coalition: The reservation utility for the ethnic (income class) partner (e.g. if i=AR, ethnic partner is AP) is the value function when he rejects the offer of the agenda setter, and the game goes to the second round, where the winning coalition between the agenda setter and class (ethnic) partner is formed. The reservation utility of the agenda setter, on the other hand, is the value function when he forms a coalition with the different partner from that in the first round. Specifically, the reservation utility of the ethnic partner in the first round is:

$$\begin{aligned} \overline{u}_1(j_1) &= u_2(j_1|i, j_2) \\ &= (1 - t_2(i, j_2))Y(j_1), j_2 \neq j_1, \end{aligned}$$

and the reservation utility of the agenda setter is:

$$\begin{aligned} \overline{u}_1(i) &= u_2(i|i, j_2) \\ &= (1 - t_2(i, j_2))Y(i) + \frac{(1 - \alpha_2(i, j_2))(t_2(i, j_2) - \frac{t_2^2(i, j_2)}{2})}{n(i)}, j_2 \neq j_1. \end{aligned}$$

Lemma 1. *When there are two rounds of legislative bargaining, and when the tax rate is strictly positive, the equilibrium tax rate and share of the pie in the second round are:*

$$t_2^*(i^*, j_2^*) = 1 - n(i^*)Y(i^*) - n(j_2^*)Y(j_2^*),$$

and

$$\alpha_2^*(i^*, j_2^*) = \frac{t_2^*(i^*, j_2^*)Y(j_2^*)n(j_2^*)}{(t_2^*(i^*, j_2^*) - \frac{t_2^{*2}(i^*, j_2^*)}{2}) \cdot Y}.$$

Proof. See Appendix. □

So now, we know that in the second round, the agenda setter offers $T_2^*(i^*, j_2^*) = \{t_2^*(i^*, j_2^*),\ \tau_2(h|i^*, j_2^*)\}$ for all h.

Lemma 2. *When there are two rounds of legislative bargaining, and when the tax rate is strictly positive, the equilibrium tax rate and share of the pie the partner gets are:*

$$\begin{aligned} t_1(i^*, j_1^*) &= 1 - n(i^*)Y(i^*) - n(j_1^*)Y(j_1^*), \\ \alpha_1(i^*, j_1^*) &= \frac{(t_1(i^*, j_1^*) - t_2(i^*, j_1^*))Y(j_1^*)n(j_1^*)}{t_1(i^*, j_1^*) - \frac{t_1^2(i^*, j_1^*)}{2})} \ \textit{if}\ n(j_2^*)Y(j_2^*) > n(j_1^*)Y(j_1^*), \end{aligned}$$

and

$$\begin{aligned} t_1(i^*, j_1^*) &= t_2(i^*, j_2^*) = 1 - n(i^*)Y(i^*) - n(j_2^*)Y(j_2^*), \\ \alpha_1(i^*, j_1^*)) &= 0 \ \textit{otherwise.} \end{aligned}$$

Proof. See Appendix. □

Proposition 2. *In the game where there are two rounds of legislative bargaining, when the tax rate is strictly positive, and the agenda setter strictly prefers to join the game, the agenda setter chooses a partner whose income level is higher and whose population size is larger in the first round:*

$$j_1 = \widetilde{j} \ if \ n(\widetilde{j})Y(\widetilde{j}) > n(\widehat{j})Y(\widehat{j}),$$

and

$$j_1 = \widehat{j} \ if \ n(\widetilde{j})Y(\widetilde{j}) < n(\widehat{j})Y(\widehat{j}).$$

Proof. See Appendix. □

In the literature of political coalition formation, it has been often argued why we see oversized coalitions even though theory suggests that a coalition should be formed with a minimal winning coalition. Actually, Sjölin (1993), Volden and Carrubba (2004) and many others show that in reality, it often happens that the coalition formations in developed countries such as Denmark and Sweden are not minimal winning coalitions, i.e., the agenda setter has a chance to choose a partner group with a small population size, but it chooses a partner with a large population size. Interestingly, this phenomenon occurs not only at the country level but also at the local government level. For example, Soren, Skjaveland, and Blom-Hansen (2008) show that in the election of the local government in Denmark, oversized coalitions were also seen, which they could not explain within the logic of existing theoretical studies.

On the other hand, there are few theoretical papers trying to explain the mechanisms of oversized governments.[18] For example, similarly to this paper, Baron and Diermeier (2001) also construct a legislative bargaining model to analyze why oversized or minority governments can form. However, the main difference between this paper and theirs is that in their model, the oversized government is caused by an extreme status quo policy. In contrast, in this paper, the coalition with the larger population size can be preferred when the rich are the majority because the rich prefer lower taxes and less deadweight cost for redistribution. As argued in Volden and Carruba (2004), there are others who try to investigate the mechanisms of an oversized coalition. However, none of the existing studies' arguments for oversized coalitions are similar to this paper, and thus, this paper brings new insights.

1.3 Conclusion

In this paper, I analyze the effect of income distribution and ethnic diversity on political coalition formation and government fiscal policy, constructing two types of legislative bargaining models.

In the basic model, the agenda setter chooses the partner group which has the lower income level and a smaller population size, in other words, the lower aggregate income, because it is cheaper to persuade the group to be a partner in a winning coalition. As the income level difference between the rich and poor increases, I find that when the poor

[18] Volden and Carrubba (2004) have a nice review of the existing theories, which try to explain why oversized coalitions can be formed, and they empirically test these theories.

are the majority, a class coalition is more likely to occur.

The extended model brings a new explanation for oversized coalitions to the literature: why we see oversized coalitions in reality contrary to what the theory of minimal winning claims. When the group is large in population size and has a high income level, it has a lower reservation utility if the outside option is determined by the pay-off of a second round to the game. The larger its population size and the higher its income level, the group becomes worse off in the second round of the game, being outside of the coalition, because it pays higher taxes as a group if outside of the winning coalition.

Here, ethnicity is loosely defined as something which unites people apart from income level. Thus, this model can be extended to analyze the effect of religious, linguistic, or even the geographical differences among people. However, I exclude the possibility of a consensus government from the model: a "loose" coalition formed solely to prevent the agenda setter from forming a winning coalition. For a further extension, one can include this possibility to enrich the analysis. Some of the empirical findings still have not been explained by existing studies, and thus, this is another perspective to be investigated further.

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Appendix A

Proof of Proposition 1. In this case, the value function of the agenda setter would be

$$u(i^*) = (1 - t(i^*,\ j^*))Y(i^*) + \frac{(1 - \alpha(i^*,\ j^*))(\ t(i^*,\ j^*) - \frac{t^2(i^*,\ j^*)}{2}) \cdot Y}{n(i^*)}, \tag{A1}$$

where $1-\alpha$ is the proportion of the net tax revenue which the agenda setter gets from the incentive compatibility constraint of the partner group which binds in this case, because if it does not bind, the agenda setter all the time has an incentive to decrease α, until it binds.

$$u(j^*) = \overline{u}(j^*) \tag{A2}$$

$$\begin{aligned}
\Leftrightarrow \quad & (1 - t(i^*,\ j^*))Y(j^*) + \frac{\alpha(i^*,\ j^*)(t(i^*,\ j^*) - \frac{t^2(i^*,\ j^*)}{2}) \cdot Y}{n(\ j^*)} = Y(j^*) \\
\Leftrightarrow \quad & \frac{\alpha(t(i^*,\ j^*) - \frac{t^2(i^*,\ j^*)}{2}) \cdot Y}{n(i^*)} = \frac{t(i^*,\ j^*)Y(j^*)n(j^*)}{n(i^*)}.
\end{aligned}$$

After substituting A2 into A1, and taking the first-order condition of (1.5), this gives us the equilibrium tax rate:

$$t(i^*,\ j^*) = \frac{Y - n(i^*)Y(i^*) - n(j^*)Y(j^*)}{Y} > 0. \tag{A3}$$

Further, the proportion the partner gets is:

$$\alpha(i^*,\ j^*) = \frac{t(i^*,\ j^*)Y(j^*)n(j^*)}{(t(i^*,\ j^*) - \frac{t^2(i^*,\ j^*)}{2})} > 0.$$

The utility difference of the agenda setter in this case and under the status quo policy is:

$$\begin{aligned}
& -t(i^*,\ j^*)Y(i^*) + \frac{t(i^*,\ j^*) - \frac{t^2(i^*,\ j^*)}{2} - t(i^*,\ j^*)Y(j^*)n(j^*)}{n(i^*)} \\
= \quad & \frac{t(i^*,\ j^*)}{n(i^*)}(1 - n(i^*)Y(i^*) - Y(j^*)n(j^*) - \frac{1 - n(i^*)Y(i^*) - n(j^*)Y(j^*)}{2}) \\
= \quad & \frac{t^2(i^*,\ j^*)}{2n(i^*)} > 0.
\end{aligned}$$

Thus, the agenda setter is better off. $\alpha(i^*,\ j^*)$ is such that the partner is indifferent between this case and the status quo policy, and thus, it is shown that the solution satisfies all the constraints.

On the other hand, the utility difference of the agenda setter when the partner has the same ethnic attribute, and when the partner belongs to the same income group is defined by

$$\Delta = u(i^*|i^*, \widetilde{j^*}\ ) - u(i^*|i^*, \widehat{j^*}),$$

which implies

$$\Delta = -(t(i^*, \widetilde{j^*}\ ) - t(i^*, \widehat{j^*}))Y(i^*)$$
$$+\frac{(1-\alpha(i^*, \widetilde{j^*}\ ))(t(i^*, \widetilde{j^*}\ ) - \frac{t^2(i^*, \widetilde{j^*})}{2})}{n(i^*)} - \frac{(1-\alpha(i^*, \widehat{j^*})(t(i^*, \widehat{i^*}) - \frac{t^{2(i^*, \widehat{j^*})}}{2})}{n(i^*)},$$

or

$$\begin{aligned}\Delta = & \frac{t(i^*, \widetilde{j^*}\ ) - t(i^*, \widehat{j^*})}{n(i^*)}(-n(i^*)Y(i^*) + 1 - \frac{t(i^*, \widetilde{j^*}\ ) + t(i^*, \widehat{j^*})}{2}) \\ & -\frac{t(i^*, \widetilde{j^*}\ )n(\widetilde{j^*}\ )Y(\widetilde{j^*}\ ) + t(i^*, \widehat{j^*})n(\widehat{j^*})Y(\widehat{j^*})}{n(i^*)}.\end{aligned} \quad \text{(A4)}$$

where $t(i^*, \widetilde{j^*}\ )$ denotes the equilibrium tax rate when the agenda setter chooses an ethnic partner, and $t(i^*, \widehat{j^*})$ denotes the tax rate when the partner belongs to the same income group as the agenda setter. Now I try to decompose the second term. Note that

$$\begin{aligned} t(i^*, \widetilde{j^*}\ ) &= 1 - n(i^*)Y(i^*) - n(\widetilde{j^*})Y(\widetilde{j^*}) \\ &= n(k)Y(k) + n(\widehat{j^*})Y(\widehat{j^*}),\ \ k \neq i^*, \widetilde{j^*}, \widehat{j^*}, \end{aligned}$$

and

$$\begin{aligned} t(i^*, \widehat{j^*}) &= 1 - n(i^*)Y(i^*) - n(\widehat{j^*})Y(\widehat{j^*}) \\ &= n(k)Y(k) + n(\widetilde{j^*})Y(\widetilde{j^*}), \end{aligned}$$

where k is the group which is outside of the coalition all the time, $k \neq i^*, \widetilde{j^*}, \widehat{j^*}$. Thus,

$$t(i^*, \widetilde{j^*}\ ) - t(i^*, \widehat{j^*}) = n(\widehat{j^*})Y(\widehat{j^*}) - n(\widetilde{j^*})Y(\widetilde{j^*}),$$

and

$$t(i^*,\widetilde{j^*}\ )+t(i^*,\widehat{j^*})=2n(k)Y(k)+n(\widetilde{j^*})Y(\widetilde{j^*})+n(\widehat{j^*})Y(\widehat{j^*}),\ \ k\neq i^*,\widetilde{j^*},\widehat{j^*}.$$

So, at the end, the second term of A4 becomes

$$\begin{aligned}
&-\frac{t(i^*,\widetilde{j^*}\ )n(\widetilde{j^*}\ )Y(\widetilde{j^*}\ )+t(i^*,\widehat{j^*})n(\widehat{j^*})Y(,\widehat{j^*})}{n(i^*)}\\
=\ &\frac{-(n(k)Y(k)+n(\widehat{j^*})Y(\widehat{j^*}))n(\widetilde{j^*}\ )Y(\widetilde{j^*}\ )+(n(k)Y(k)+n(\widetilde{j^*})Y(\widetilde{j^*}))n(\widehat{j^*})Y(\widehat{j^*})}{n(i^*)}\\
=\ &\frac{n(k)Y(k)}{n(i^*)}(n(\widehat{j^*})Y(\widehat{j^*})-n(\widetilde{j^*}\ )Y(\widetilde{j^*}\ ))\\
=\ &\frac{n(k)Y(k)}{n(i^*)}(t(i^*,\widetilde{j^*}\ )-t(i^*,\widehat{j^*})),\ \ k\neq i^*,\widetilde{j^*},\widehat{j^*}.
\end{aligned}$$

Thus substituting back the expression into A4 would give us:

$$\begin{aligned}
\Delta\ &=\ \frac{t(i^*,\widetilde{j^*}\ )-t(i^*,\widehat{j^*})}{n(i^*)}(-n(i^*)Y(i^*)+1-\frac{t(i^*,\widetilde{j^*}\ )+t(i^*,\widehat{j^*})}{2}+n(k)Y(k))\\
&=\ \frac{t(i^*,\widetilde{j^*}\ )-t(i^*,\widehat{j^*})}{n(i^*)}(1-n(i^*)Y(i^*)-\frac{n(\widetilde{j^*})Y(\widetilde{j^*})+n(\widehat{j^*})Y(\widehat{j^*})}{2}),
\end{aligned}$$

which is positive if and only if $t(i^*,\widetilde{j^*}\ )-t(i^*,\widehat{j^*})>0\Leftrightarrow n(\widehat{j^*})Y(\widehat{j^*})>n(\widetilde{j^*})Y(\widetilde{j^*})$. In sum,

$$\Delta>0 \text{ iff } n(\widehat{j^*})Y(\widehat{j^*})>n(\widetilde{j^*})Y(\widetilde{j^*}).$$

□

Proof of Corollary 1. The condition of Proposition 1, when the ethnic partner is preferred can be changed into

$$\frac{n(\widehat{i^*})}{n(\widetilde{i^*})}>\frac{Y(\widetilde{i^*})}{Y(\widehat{i^*})}.$$

Now, when the poor are the majority, this condition becomes

$$\frac{n(AP)}{n(BR)} > \frac{Y(R)}{Y(P)}.$$

It is quite obvious that as the income difference becomes larger, this condition is unlikely to be satisfied.

When the rich are the majority, the condition becomes

$$\frac{n(BR)}{n(AP)} > \frac{Y(P)}{Y(R)},$$

and it is quite obvious that as the income difference becomes larger, an ethnic coalition would be preferred. □

Proof of Lemma1. To find sub-game, perfect equilibrium, I solve the game by backward induction. In this case, the value function of the agenda setter would be

$$u_2(i^*) = (1 - t_2(i^*,\ j_2^*))Y(i^*) + \frac{(1 - \alpha_2(i^*,\ j_2^*))(\ t_2(i^*,\ j_2^*) - \frac{t_2^2(i^*,\ j_2^*)}{2}) \cdot Y}{n(i^*)}, \tag{A5}$$

where α_2 is the proportion of the net tax revenue which the agenda setter gets from the incentive compatibility constraint of the partner group which binds in this case, because if it does not bind, the agenda setter would have incentive to decrease the $\alpha_2(i^*,\ j^*)$ till it binds.

$$u_2(j_2^*) = \overline{u}_2(j_2^*),$$

which implies

$$(1 - t_2(i^*,\ j_2^*))Y(j^*) + \frac{\alpha_2(i^*,\ j_2^*)(t_2(i^*,\ j_2^*) - \frac{t_2^2(i^*,\ j_2^*)}{2}) \cdot Y}{n(\ j_2^*)} = Y(\ j_2^*)$$

and

$$\frac{\alpha_2(i^*,\ j_2^*)(t_2(i^*,\ j_2^*) - \frac{t_2^2(i^*,\ j_2^*)}{2}) \cdot Y}{n(i^*)} = \frac{t_2(i^*,\ j_2^*)Y(j_2^*)n(j_2^*)}{n(i^*)}. \tag{A6}$$

After substituting A6 into A5, and taking the first-order condition of (4) gives us the equilibrium tax rate:

$$t_2(i^*,\ j_2^*) = \frac{Y - n(i^*)Y(i^*) - n(j_2^*)Y(j_2^*)}{Y}.$$

To sum up,

$$t_2^*(i,j) = 1 - n(i^*)Y(i^*) - n(j_2^*)Y(j_2^*),$$

and

$$\alpha_2(i^*,\ j_2^*) = \frac{t_2(i^*,\ j_2^*)Y(j_2^*)n(j_2^*)}{\alpha_2(i^*,\ j_2^*)(t_2(i^*,\ j_2^*) - \frac{t_2^2(i^*,\ j_2^*)}{2})}.$$

Further, given $t_2(i^*,\ j^*) > 0, \alpha_2^*(i,j) = \frac{t_2^*(i,j)Y(j)n(j)}{(t_2^*(i,j) - \frac{t_2^{*2}(i,j)}{2})\cdot Y}. > 0,$

$$\begin{aligned}
u_2(i^*) - u(i|q) &= (1 - t_2(i^*,\ j^*))Y(i^*) + \frac{(\ t_2(i^*,\ j^*) - \frac{t_2^2(i^*,\ j^*)}{2}) \cdot Y - t_2^*(i,j)Y(j^*)n(j^*)}{n(i^*)} - Y(i^*) \\
&= \frac{1}{n(i^*)}(t_2(i^*,\ j^*)(-n(i^*)Y(i^*) - Y(j^*)n(j^*) + 1) - \frac{t_2^2(i^*,\ j^*)}{2n(i^*)} \\
&= \frac{t_2^2(i^*,\ j^*)}{n(i^*)} - \frac{t_2^2(i^*,\ j^*)}{2n(i^*)} > 0.
\end{aligned}$$

It is shown above that the agenda setter is better off forming a coalition in the second round than being under the default policy, and thus, chooses to form a coalition in the second round. □

Proof of Lemma 2. Lagrangian of the first round of the game is:

$$L = u_1(i|i,j_1) + \lambda_1(u_1(i|i,j_1) - Y(i)) + \lambda_2(u_1(j_1|i,j_1) - \overline{u}(j_1)) + \lambda_3 t_1(i,j_1) + \lambda_4\alpha_1(i,j_1) \tag{A7}$$

Kuhn-Tucker conditions are:

$$\begin{aligned}
L_{t_1} = -Y(i) + \frac{(1-\alpha_1(i,j_1))(1-t_1(i,j_1))}{n(i)} + \lambda_1(-Y(i) + \frac{(1-\alpha_1(i,j))(1-t_1(i,j))}{n(i)}) \\
+\lambda_2(-Y(j_1) + \frac{\alpha_1(i,j_1)(1-t_1(i,j_1))}{n(j)}) + \lambda_3 \leq 0, \qquad \text{(A8)}
\end{aligned}$$

$$L_{t_1} \cdot t_1 = 0 \tag{A9}$$

$$L_{\alpha_1} = \frac{-(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(i)} + \lambda_1 \cdot \frac{-(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(i)}$$

$$+\lambda_2 \cdot \frac{t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2}}{n(j_1)} + \lambda_4 \leq 0, \tag{A10}$$

$$L_{\alpha_1} \cdot \alpha_1(i,j_1) = 0, \tag{A11}$$

$$L_{\lambda_1} = -(t_1(i,j_1) - t_2(i,j_2))Y(i)$$

$$+\frac{(1-\alpha_1(i,j_1))(t_1(i,j_1) - \frac{t_1(i,j_1)}{2}) - (1-\alpha_2(i,j_2))(t_2(i,j_2) - \frac{t_2(i,j_2)}{2})}{n(i)} \geq 0, \tag{A12}$$

$$L_{\lambda_1} \cdot \lambda_1 = 0, \tag{A13}$$

$$L_{\lambda_2} = -(t_1(i,j_1) - t_2(i,j_2))Y(j) + \frac{\alpha_{11}(i,j_1)(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(j)} \geq 0, \tag{A14}$$

$$L_{\lambda_2} \cdot \lambda_2 = 0, \tag{A15}$$

$$L_{\lambda_3} = t_1(i,j_1) \geq 0, \tag{A16}$$

$$L_{\lambda_3} \cdot \lambda_3 = 0, \tag{A17}$$

$$L_{\lambda_4} = \alpha_1(i,j_1) \geq 0, \tag{A18}$$

$$L_{\lambda 4} \cdot \lambda_4 = 0 \tag{A19}$$

$$\lambda_1 \geq 0, \lambda_2 \geq 0, \lambda_3 \geq 0, \lambda_4 \geq 0, \tag{A20}$$

where $\widehat{j}$ is the income class partner of i.

1. when $\alpha_1(i,j_1) = 0$,

   (A10) becomes $L_{\alpha_1} = \frac{-(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(i)} + \lambda_1 \cdot \frac{-(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(i)} + \lambda_2 \cdot \frac{t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2}}{n(j_1)} + \lambda_4 \leq 0$

   (a) when $t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2} = 0$, then $t_1(i,j_1) = 0$ or 2.

   In this case, $L_{\alpha_1} = \lambda_4 \leq 0$, on the other hand, from (A20) $\lambda_4 \geq 0$, and thus $\lambda_4 = 0$

      i. when $t_1(i,j_1) = 0$

      (A15) becomes $L_{\lambda_2} = t_2(i,j_2)Y(j_2) > 0 \Leftrightarrow \lambda_2 = 0$

      In this case, (A8) becomes $L_{t_1} = (1+\lambda_1)(-Y(i) + \frac{1}{n(i)}) + \lambda_3 = \frac{(1+\lambda_1)}{n(i)}(1 - n(i)Y(i)) + \lambda_3$, which is strictly positive, given (A20) and $1 - n(i)Y(i) > 0$. However, this does not satisfy the condition (A8) so this is not a solution.

      ii. when $t_1(i,j_1) = 2$

      In this case, (A14) becomes $L_{\lambda_2} = -(2 + t_2(i,j_2)Y(j_2)$ which is strictly negative, given that $t_2(i,j_2) = 1 - n(i)Y(i) - n(j_2)Y(j_2)$,which is a contradiction to condition (A14), so this is not the solution.

(b) when $t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2} > 0$,(A8)-(A20) becomes

$L_{\lambda_3} = t_1(i,j_1) > 0 \Leftrightarrow \lambda_3 = 0$

$L_{t_1} = -Y(i) + \frac{(1-t_1(i,j_1))}{n(i)} + \lambda_1(-Y(i) + \frac{(1-t_1(i,j_1))}{n(i)}) + \lambda_2(-Y(j_1)) = 0,$

$L_{\lambda_1} = -(t_1(i,j_1) - t_2(i,j_2))Y(i) + \frac{(1-\alpha_1(i,j_1))(t_1(i,j_1) - \frac{t_1(i,j_1)}{2}) - (1-\alpha_2(i,j_2))(t_2(i,j_2) - \frac{t_2(i,j_2)}{2})}{n(i)} \geq 0,$

$L_{\lambda_2} = -(t_1(i,j_1) - t_2(i,j_2))Y(j_1) \geq 0$

$L_{\lambda_4} = \alpha_1(i,j_1) = 0$

$L_{\alpha_1} = \frac{-(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(i)} + \lambda_1 \cdot \frac{-(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(i)} + \lambda_2 \cdot \frac{t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2}}{n(j_1)} + \lambda_4 \leq 0,$

i. When $t_1(i,j_1) > t_2(i,j_2)$, then $L_{\lambda_2} < 0$. So this is not a solution.

ii. When $t_1(i,j_1) < t_2(i,j_2)$, then $\lambda_2 = 0$

$L_{t_1} = (1+\lambda_1)(-Y(i) + \frac{(1-t_2(i,j_2))}{n(i)}) = 0$

$\Leftrightarrow t_1(i,j_1) = 1 - n(i)Y(i) > t_2(i,j_2),$

so this is not a solution.

iii. When $t_1(i,j_1) = t_2(i,j_2)$

(A8) becomes $L_{t_1} = (1+\lambda_1)(-Y(i) + \frac{(1-t_2(i,j_2))}{n(i)}) + \lambda_2(-Y(j_1)) = (1+\lambda_1)n(j_1)Y(j_1) + \lambda_2(-Y(j_1)) = 0$

$\Leftrightarrow \lambda_2 = (1+\lambda_1)n(j_1).$

Further, in this case $L_{\lambda_1} = \frac{\alpha_2(i,j_2))(t_2(i,j_2) - \frac{t_2(i,j_2)}{2})}{n(i)} > 0,$

which satisfies the conditions.

Solution: $t_1(i^*,j_1^*) = t_2(i^*,j_2^*) = 1 - n(i^*)Y(i^*) - n(j_2^*)Y(j_2^*)$

$\alpha_1(i^*,j_1^*) = 0,\ \lambda_1 \geq 0, \lambda_2 = (1+\lambda_1)n(j_1^*), \lambda_3 = 0, \lambda_4 \geq 0.$

2 When $\alpha_1 > 0$,

then $L_{\lambda_4} > 0$, which implies $\lambda_4 = 0$ and since $L_{\alpha_1} \cdot \alpha_1 = 0$ and $\alpha_1 > 0$, then $L_{\alpha_1} = 0$.

(a) When $t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2} = 0$, then $t_1(i,j_1) = 0$ or 2. $L_{\alpha_1} = \lambda_4 = 0$.

i. When $t_1(i,j_1) = 0,\ L_{\lambda_2} = t_2(i,j_2)Y(j_2) > 0 \Leftrightarrow \lambda_2 = 0.$

$L_{t_1} = -Y(i) + \frac{(1-\alpha_1(i,j_1))}{n(i)} + \lambda_1(-Y(i) + \frac{1-\alpha_1(i,j_1)}{n(i)}) + \lambda_3 \leq 0$

$L_{\lambda_1} = t_2(i,j_2))Y(i) - \frac{(1-\alpha_2(i,j_2))(t_2(i,j_2) - \frac{t_2(i,j_2)}{2})}{n(i)} < 0,$

so this is not a solution.

ii. when $t_1(i,j_1) = 2$, then $L_{\lambda_3} > 0 \Leftrightarrow \lambda_3 = 0$.

In this case, $L_{\lambda_2} = -(2 + t_2(i,j_2))Y(j_2) < 0$, which is a contradiction, so this is not the solution

(b) when $t(i,j_1) - \frac{t_1^2(i,j_1)}{2} > 0$ then $L_{\lambda_3} > 0 \Leftrightarrow \lambda_3 = 0$

Since $\alpha_1 > 0$ (A10) becomes

$$\begin{aligned} L_{\alpha_1} &= \frac{-(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(i)} + \lambda_1 \cdot \frac{-(t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2})}{n(i)} + \lambda_2 \cdot \frac{t_1(i,j_1) - \frac{t_1^2(i,j_1)}{2}}{n(j_1)} = 0, \\ \Leftrightarrow \frac{(1+\lambda_1)}{\lambda_2} &= \frac{n(i)}{n(j_1)}. \end{aligned}$$

On the other hand, since $t(i,j_1) > 0$, (A8) becomes

$$\begin{aligned} L_{t_1} = -Y(i) + \frac{(1-\alpha(i,j_1))(1-t_1(i,j_1))}{n(i)} &+ \lambda_1(-Y(i) + \frac{(1-\alpha_1(i,j_1))(1-t_1(i,j_1))}{n(i)}) \\ +\lambda_2(-Y(j_1) + \frac{\alpha_1(i,j_1)(1-t_1(i,j_1))}{n(j_1)}) &= 0 \\ \Leftrightarrow \frac{(1+\lambda_1)}{\lambda_2} &= -\frac{-Y(j_1) + \frac{\alpha_1(i,j_1)(1-t_1(i,j_1))}{n(j)}}{-Y(i) + \frac{(1-\alpha_1(i,j_1))(1-t_1(i,j_1))}{n(i)}}. \end{aligned}$$

Thus,

$$\begin{aligned} \frac{n(i)}{n(j)} &= \frac{-Y(j_1) + \frac{\alpha(i,j_1)(1-t_1(i,j_1))}{n(j)}}{-Y(i) + \frac{(1-\alpha_1(i,j_1))(1-t_1(i,j_1))}{n(i)}} \\ &\Leftrightarrow -n(i)Y(i) + (1-\alpha_1(i,j_1))(1-t_1(i,j_1)) = n(j_1)Y(j_1) - \alpha_1(i,j_1)(1-t_1(i,j_1)) \\ &\Leftrightarrow t_1(i,j_1) = 1 - n(i)Y(i) - n(j_1)Y(j_1). \end{aligned}$$

i. When $\lambda_2 = 0$, then
(A8) becomes
$L_{t_1} = -Y(i) + \frac{(1-\alpha_1(i,j_1))(1-t_1(i,j_1))}{n(i)} + \lambda_1(-Y(i) + \frac{(1-\alpha_1(i,j_1))(1-t_1(i,j_1))}{n(i)}) = 0$
since $t_1(i,j_1) > 0$
$\Leftrightarrow \lambda_1 = -1 < 0$, which does not satisfy the conditions, so this is not a solution.

ii. When $\lambda_2 > 0$, then (A14) becomes

$$
\begin{aligned}
L_{\lambda_2} &= -(t_1(i,j_1)-t_2(i,j_2))Y(j_1)+\frac{\alpha_1(i,j_1)(t_1(i,j_1)-\frac{t_1^2(i,j_1)}{2})}{n(j_1)}=0\\
&\Leftrightarrow \alpha_1(i,j_1)(t_1(i,j_1)-\frac{t_1^2(i,j_1)}{2})=(t_1(i,j_1)-t_2(i,j_2))Y(j_1).
\end{aligned}
$$

(A) When $\lambda_1 > 0$, then (A12) implies

$$
L_{\lambda_1} = -(t_1(i,j_1)-t_2(i,j_2))Y(i)
$$
$$
+\frac{(1-\alpha_1(i,j_1))(t_1(i,j_1)-\frac{t_1(i,j_1)}{2})-(1-\alpha_2(i,j_2))(t_2(i,j_2)-\frac{t_2(i,j_2)}{2})}{n(i)}=0.
$$

In other words, the incentive constraint of the agenda setter binds. In this case, the value function of the agenda setter is:

$$
u_1(i|i,j_1)=u_2(i|j_2).
$$

However, this case is apparently dominated by the solution in the case 1b(iii), where the agenda setter is strictly better off than in the second round, and thus, this is not a solution.

(B) When $\lambda_1 = 0$,(A10) implies

$$
\begin{aligned}
L_{\alpha_1} &= \frac{-(t_1(i,j_1)-\frac{t_1^2(i,j_1)}{2})}{n(i)}+\lambda_2\cdot t_1(i,j_1)-\frac{t_1^2(i,j_1)}{2}=0\\
&\Leftrightarrow \lambda_2=\frac{n(j_1)}{n(i)}.
\end{aligned}
$$

(A8) becomes

$$
\begin{aligned}
L_{t_1} &= -Y(i)+\frac{(1-\alpha_1(i,j_1))((1-t_1(i,j_1))}{n(i)}+\lambda_2(-Y(j_1)\\
&\quad+\frac{\alpha_1(i,j_1)(1-t_1(i,j_1))}{n(j_1)})=0\\
&\Leftrightarrow n(i)Y(i)-(1-\alpha_1(i,j_1))(1-t_1(i,j_1))=-n(j)Y(j)+\alpha_1(i,j)(1-t_1(i,j_1))\\
&\Leftrightarrow t_1(i,j_1)=1-n(i)Y(i)-n(j_1)Y(j_1).
\end{aligned}
$$

Further, in this case, $\alpha_1(i,j_1)(t_1(i,j_1)-\frac{t_1^2(i,j_1)}{2}) = (t_1(i,j_1)-t_2(i,j_2))Y(j_1)n(j_1)$. Note that to satisfy the constraint of $\alpha_1(i,j_1) > 0$, this solution is plausible only when $t_1(i,j_1) > t_2(i,j_2) \Leftrightarrow n(j_2)Y(j_2) > n(j_1)Y(j_1)$.

Now, we have 2 solution candidates, 2(b)(ii)(B)- $t_1(i,j_1) = 1-n(i)Y(i)-n(j_1)Y(j_1)$, $\alpha_1(i,j_1)(t_1(i,j_1)-\frac{t_1^2(i,j_1)}{2}) = (t_1(i,j_1)-t_2(i,j_2))Y(j_1)n(j_1)$ and 1(b)(iii)- $t_1(i,j_1) = t_2(i,j_2) = 1-n(i)Y(i)-n(j_2)Y(j_2), \alpha_1(i,j_1) = 0$, and the expected utility difference of the agenda setter in the case of 2(b)(ii)(B) is all the time larger than 1(b)(iii). However, 2(b)(ii)(B) is plausible only when $t_1(i,j_1) = t_2(i,j_2)$.

So to sum up,

$t_1(i,j_1) = 1-n(i)Y(i)-n(j_1)Y(j_1)$, $\alpha_1(i,j_1)(t_1(i,j_1)-\frac{t_1^2(i,j_1)}{2}) = (t_1(i,j_1)-t_2(i,j_2))Y(j_1)n(j_1)$ when $n(j_2)Y(j_2) > n(j_1)Y(j_1)$,

$t_1(i,j_1) = 1-n(i)Y(i)-n(j_2)Y(j_2), \alpha_1(i,j_1) = 0$ otherwise. □

Proof of Proposition 2. If we define the utility difference of the agenda setter when he chooses the ethnic partner as a partner to form a coalition and an income class partner as a partner for the coalition when $n(\widehat{i})Y(\widehat{i}) > n(\widetilde{i})Y(\widetilde{i})$:

$$\Delta \equiv u_1(i|i,\widetilde{i}) - u_1(i|i,\widehat{i})$$

$$= (1-t_1(i,\widetilde{i}))Y(i) + \frac{(1-\alpha_1(i,\widetilde{i}))(t_1(i,\widetilde{i})-\frac{t_1^2(i,\widetilde{i})}{2})}{n(i)} - (1-t_1(i,\widehat{i}))Y(i) - \frac{(t_1(i,\widehat{i})-\frac{t_1^2(i,\widehat{i})}{2})}{n(i)}$$

$$\{t_1(i,\widetilde{i}) = t_1(i,\widehat{i})\}$$

$$= -\frac{\alpha_1(i,\widetilde{i})(t_1(i,\widetilde{i})-\frac{t_1^2(i,\widetilde{i})}{2})}{n(i)} < 0.$$

Thus, the ethnic partner is preferred in case of $n(\widehat{i})Y(\widehat{i}) > n(\widetilde{i})Y(\widetilde{i})$. On the other hand, when $n(\widehat{i})Y(\widehat{i}) < n(\widetilde{i})Y(\widetilde{i})$,

$$\Delta \equiv u_1(i|i,\widetilde{i}) - u_1(i|i,\widehat{i})$$

$$= (1-t_1(i,\widetilde{i}))Y(i) + \frac{(t_1(i,\widetilde{i})-\frac{t_1^2(i,\widetilde{i})}{2})}{n(i)} - (1-t_1(i,\widehat{i}))Y(i) - \frac{(1-\alpha_1(i,\widehat{i}))(t_1(i,\widehat{i})-\frac{t_1^2(i,\widehat{i})}{2})}{n(i)}$$

$$= \frac{\alpha_1(i,\widehat{i})(t_1(i,\widetilde{i})-\frac{t_1^2(i,\widetilde{i})}{2})}{n(i)} > 0.$$

In the case of $n(\widehat{i})Y(\widehat{i}) < n(\widetilde{i})Y(\widetilde{i})$, the class partner is preferred, and thus, the summary is that the group with larger population size and higher income level is preferred when forming the coalition. $\square$

Appendix B

Table 1.1: Coalition Type across Regions (1975-2006)

Region	Non-economic Coalition Share (%)			# Obs.
	1975-1990	1991-2006	1975-2006	
The Middle East and Africa	64.7	76.9	73.5	75
Latin America and the Caribbean	33.9	69.1	55.2	268
East Asia and Pacific	80.4	69.3	72.9	65
South Asia	84.4	64.5	63.1	53
Europe (non-high income) and Central Asia	40.0	77.8	76.6	225
OECD and High-Income Countries	47.4	46.5	46.8	849
Total	54.2	65.2	50.2	1527

Note: Single party government is excluded from the sample.

Data source: DPI2006, Database of Political Institutions, World Bank Research Group

Table 1.2: The Share of Oversized Coalitions (1975-2006)

Region	Oversized Coalition Share (%)			# Obs
	1975-1990	1991-2006	1975-2006	
The Middle East and Africa	56.1	61.5	60.4	378
Latin America and the Caribbean	57.6	45.8	48.4	223
East Asia and Pacific	41.4	55.2	51.4	179
South Asia	22.2	34.4	28.3	256
Europe (non-high income) and Central Asia	20.0	31.8	31.8	179
OECD and high income countries	32.9	26.1	29.5	651
Total	39.5	41.0	40.8	1866

Note: The samples consist of coalition governments.

Data source: DPI2006, Database of Political Institutions, World Bank Research Group

Table 1.3: The Gini Coefficients across Regions (1975-2006)

Region	Income inequality - Gini coefficients			# Obs
	1975-1990	1991-2006	1975-2006	
Sub-Saharan Africa	52.7	51.4	52.1	226
Latin America and the Caribbean	54.9	55.8	55.4	331
East Asia & Pacific	31.8	39.3	35.4	32
South Asia	35.5	30.0	33.5	25
Europe (non-high income) and Central Asia	38.9	40.9	40.0	401
OECD and high income countries	30.2	30.6	30.4	1043
Total	37.9	39.0	38.5	2058

Note: The unit of observation is country x year.

Data source: World Income Inequality Databases (WIID)2

Chapter 2

Reponses to More Sever Punishment in the Courtroom: Evidence from Truth-in-Sentencing Laws

Fusako Tsuchimoto Menkyna and Libor Dušek

Abstract

We investigate the behavioral responses of judges and prosecutors to more severe punishments by analyzing the effects of Truth-in-Sentencing (TIS) laws in a large sample of criminal cases in the U.S. The TIS laws raised the severity of punishment by requiring offenders to serve at least 85 percent of their imposed sentences in prison. Differences between the U.S. states in the timing of adoption and the types of crimes covered provide a source of identification. The key findings are: (1) The TIS laws reduced the probability that an arrested offender is eventually convicted by 9 percent through an increase in the probability that the case is dismissed, a reduction in the probability that the defendant pleads guilty, and a reduction in the probability that the defendant is convicted at trial. (2) The TIS laws reduced the imposed sentence that a defendant can expect upon arrest by 8 percent. (3) These effects were more pronounced for crimes that were not the primary target of the TIS law, i.e., non-violent crimes.

Keywords: criminal procedure, criminal law, sentencing, Truth-in-Sentencing laws

2.1 Introduction

Laws that impose more severe punishments on criminals sometimes bring unexpected consequences. Their direct objective—to deter and incapacitate offenders by keeping them longer in prison—may be mitigated by behavioral responses of judges, jurors, and prosecutors who exercise a certain amount of discretion at various stages of the criminal procedure. Judges and jurors may become more reluctant to convict, judges may impose a shorter sentence, and prosecutors may adjust their plea bargaining tactics. Understanding the character and empirical magnitude of the behavioral responses has important policy implications. Since legislators cannot fully control the choices of judges, jurors, and prosecutors, they should take the mitigating responses into account when designing sentencing policies. Legislating longer sentences may be undesirable both on the grounds of efficiency as well as fairness if the mitigating responses are large enough.

This paper presents evidence on mitigating responses by evaluating the effects of the so-called Truth-in-Sentencing (TIS) laws on the outcomes of criminal cases. The TIS laws, adopted by many U.S. states during the 1990s, require convicted offenders to serve at least 85 percent of their imposed prison sentence. This implies a stark increase in the fraction of the sentence served compared to the 1980s and early 1990s when prisoners served 48 percent on average (Ditton and Wilson 1999), mostly due to discretionary early release by parole officers and by prison overcrowding. If the probability of conviction and the imposed sentences had not changed after introducing the TIS laws, an offender could spend 70 percent more time in prison than previously expected.

Several states such as Utah and the federal government imposed TIS-type requirements prior to the 1990s (U.S. Department of Justice, 1993). The Federal Violent Crime Control and Law Enforcement Act of 1994[1] encourages more states to adopt such provisions by introducing the so-called Violent Offenders Incarceration and the Truth-in-Sentencing Incentive Grant Program. To be eligible for the TIS grant, a state has to implement a TIS law that requires offenders convicted of a Part I violent crime[2] to serve no less than 85 percent of the sentence imposed, or a similar law that effectively resulted in such offenders serving on average at least 85 percent of the sentence.[3]

The timing of adoption of the TIS laws by individual states varied (see Table 2.1). While only two states (plus the District of Columbia) had TIS-type provisions in the

[1]Public Law 103-322, Sept. 13, 1994 (the "1994 Crime Act").

[2]Part I violent crime includes murder, rape, robbery, and assault.

[3]For more detail on the criteria, see the U.S. Department of Justice (2005).

early 1990s, eleven other states adopted the TIS laws within one year of the passage of the Violent Crime Control and Law Enforcement Act of 1994. Twenty-seven states and the District of Columbia met the eligibility criteria by 1998.[4] The states also varied in the scope of coverage of the TIS laws; the 85 percent requirement applied to Part I violent felonies in all adopting states, but in some states it applied to other crimes as well.

The variation among the states in the timing of adoption and the types of crime covered allows for an identification of the effects of the TIS laws on case outcomes by a difference-in-differences-in-differences estimator. The data set—State Court Processing Statistics (SCPS)—consists of a large sample of felony cases from the most populous counties in the United States and allows a control for many observable characteristics in each case.

The paper contributes to the empirical literature on behavioral responses in criminal procedure in several ways. First, it captures the various margins of responses in the criminal justice process in two simple summary measures. One measure is the change in the probability that an arrested offender is eventually convicted, irrespective of whether at trial or by pleading guilty. Indeed, we find that it fell by 9 percent. The other measure is the change in the imposed sentence that an arrested offender receives at the final disposition of the case, which is either the actual sentence imposed on a convicted defendant or a zero sentence imposed on an offender that is not convicted. It gives a particularly useful summary of the behavioral responses as the changes in the probability of dismissal, guilty plea, conviction at trial, and the sentence imposed upon conviction are reflected into the sentence that is ultimately imposed. It can also be interpreted as a change in the sentence that an offender can expect conditional on arrest. The TIS laws reduced the imposed sentence conditional on arrest by 8 percent according to our most preferred specifications.

The behavioral responses mitigated the intended effect of the TIS laws to impose more severe punishment. In the absence of behavioral responses, the sentence actually served, conditional on arrest, would have increased by 70 percent on average. As the sentence imposed, conditional on arrest, fell by 8 percent, the sentence that an arrested offender can expect actually to serve increased not by 70 percent but by "only" 56 percent.[5]

[4] These states received $2.7 billion in total during 1996-2001 through the VOI/TIS grant program (U.S. Department of Justice, 2005).

[5] The expected sentence actually served was 50 percent of the sentence imposed upon conviction times the probability of being convicted prior to the adoption of the TIS laws. In the absence of behavioral responses, it would rise to 85 percent, a 70-percent increase. The behavioral responses reduced the product of the sentence and the probability by 8 percent. Hence, the new sentence actually served,

Therefore, the unintended behavioral responses removed about one-fifth of the intended increase in the severity of punishment. The mitigating responses are empirically relevant and need to be taken into account when designing of sentencing policies.

Second, the paper provides one of the first empirical tests of Andreoni's (1991) proposition that more severe punishment should lead to a lower probability of conviction. While the proposition is widely accepted as theory, empirical evidence has been scant at best. We identified only two empirical studies using data on actual cases. Snyder (1990) finds a reduction in the probability of conviction in antitrust cases as the level of charges for certain antitrust violations was raised from misdemeanor to felony. Bjerk (2005), who explores primarily the response of prosecutors to the three-strikes laws, also tests whether offenders qualifying for a third-strike offense face a lower probability of conviction at trial but does not find any significant effect.[6] We do find a significant decrease in the overall probability that an arrested defendant is convicted. Further, when investigating the particular channels behind this overall effect, we find that TIS laws reduce the probability of conviction through a higher probability that the case is dismissed, lower the probability that the defendant pleads guilty, and, to a lesser extent, the lower probability of conviction at trial.

Third, the paper adds new results to the empirical literature on the behavioral responses of prosecutors. One line of the literature finds that prosecutors "exploit" enhanced statutory sentences, consistently with models of the prosecutors that maximize the total punishment imposed. Kuziemko (2006) shows that defendants in murder cases in New York were accepting plea bargains with harsher terms after the state reintroduced the death penalty in 1995, while the likelihood that the defendant would plead guilty did not change. Kessler and Piehl (1998) find that California's Proposition 8, a popular initiative that mandated enhanced sentences for offenders with certain criminal histories caused an increase in sentences for those crimes that were subject to Proposition 8 as well as for crimes that were factually similar but were not subject to Proposition 8.

Another line of the literature instead finds that the prosecutors mitigate enhanced

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conditional on arrest, increased to 78 percent (92 percent of 85), which is 56 percent higher than the pre-TIS law level.

[6] Bjerk's result may plausibly be explained by sample selection. The three-strikes laws made it more likely that a felony defendant with two prior strikes would have charges reduced to a misdemeanor (resulting in cases with relatively stronger evidence being prosecuted as felonies) and that he would not accept the plea bargain (resulting in cases with relatively stronger evidence being continued to trial). The shift in the distribution of cases reaching trial shifts the probability of conviction upward, offsetting the predicted behavioral response.

statutory sentences, which is rather consistent with the view that prosecutors use their discretion to apply broader social norms of justice and fairness in punishment. Bjerk (2005) studies the impact of the three-strikes laws which dramatically enhanced prison sentences for criminals with at least two prior violent felony convictions. The prosecutors became more likely to reduce the charge from felony to misdemeanor when the defendant was at risk of receiving a three-strike sentence. Walsh (2004) documents that between 25-45 percent of offenders eligible for a three-strike sentence in urban counties in California have their prior strikes dismissed.[7]

According to our findings, the probability that the defendant would plead guilty decreased by 10 percent, and the probability that the prosecutors would reduce charges from felony to misdemeanor decreased by 4 percent. Pleading guilty apparently became a less favorable alternative to trial; these findings rather support the "exploiting" view of the prosecutors.

Fourth, the paper provides interesting results on the heterogeneity of the responses. The TIS laws are designed primarily to punish violent criminals more severely, although about one third of the states apply them to non-violent crimes as well. The behavioral responses to the TIS laws are more pronounced for non-violent crimes, i.e., those crimes at which the laws were not primarily targeted. Judges and prosecutors appear to respond more strongly when the actual content of the law deviates from its stated objectives.[8]

Last, the paper also provides several policy-relevant findings about the effects of the TIS laws themselves. So far, Shepherd (2002) has analyzed their deterrence effects. Using a county-level panel, she estimates the effect of the TIS laws on crime rates, arrest rates, and the median prison sentences. She finds that the arrest rates increased with the introduction of TIS laws as the states that introduced the TIS laws tended to adopt a "tough on crime" attitude, and the police made more effort to arrest. Similarly she finds an increase in the imposed prison sentences. Her estimates can be interpreted as evidence of judges and prosecutors not offsetting an increase in the severity of punishment;

[7]The findings by Bjerk (2005) and Walsh (2004) can alternatively be rationalized as an optimal response by prosecutors who maximize the average sentence or number of convictions at trial subject to the resource constraint. Realizing that the judge or jury will be very reluctant to convict a defendant with two prior strikes when the punishment for the third-strike offense is deemed too severe (typically a situation when the third strike is relatively a petty crime), the prosecutor anticipates that winning the case would require substantial resources that would no longer be available for other cases. Offering "softer" terms to the defendant is then optimal even for a prosecutor who maximizes the average sentence and does not necessarily indicate an intentional objective to mitigate very long sentences.

[8]Such a selective response is presumably possible only if the judges and prosecutors share the stated objective of the legislation, which apparently is the case with the TIS laws (Shepherd, 2002).

alternatively, they can be interpreted as evidence of other "tough on crime" policies that were correlated with the adoption of the TIS laws. Our empirical strategy differs from that of Shepherd; we use case-level as opposed to county-level data and our "difference-in-differences-in-differences" estimator allows us to control for the unobservable "tough on crime" policies. In addition, we provide new findings of a substantial reduction in the probability of conviction and an overall reduction in the sentence imposed conditional on arrest.Our other findings, namely the reduction in the plea rate and an overall increase in the sentences imposed upon conviction, generally concur with those of Shepherd. Owens (2010), using the same data set as we do, detects a particular response to the TIS laws in the criminal procedure—people who were arrested for an offense covered by the TIS law but pleaded guilty to a misdemeanor (to which the TIS requirement does not apply) were punished with relatively harsher sentences. Our paper instead evaluates the impact of the TIS laws on the overall punitiveness of the criminal justice process on a broader range of case outcomes.

2.2 Theoretical predictions

This section discusses the behavioral responses to the TIS laws predicted by the theoretical literature. Simple expressions of measurable case outcomes organize our thinking:

$$S^S = S^C \cdot f \tag{2.1}$$

$$E[S^S|arrest] = p \cdot S^C \cdot f = \big(p \cdot S^C + (1-p) \cdot 0\big) \cdot f = S^A \cdot f. \tag{2.2}$$

The punishment suffered by a convicted defendant is the sentence actually served in prison S^S, which is a product of the sentence imposed upon conviction S^C and the fraction of the sentence that is actually served f. The expected punishment facing an arrested defendant is the expected sentence actually served in prison $E[S^S|arrest]$, which in turn, is the product of the probability p that he is convicted (conditional on arrest), the sentence imposed if convicted, and the fraction actually served. The sentence if not convicted is, of course, zero. Adding the outcome under non-conviction to the expression in equation 2.2 shows straightforwardly that the expected sentence actually served in prison can also be stated as the expected sentence imposed (conditional on arrest) S^A multiplied by the fraction of the sentence served. The variable S^A summarizes adjustments in the probability and the sentence into a single measure of punishment that is produced as an "output" of the criminal procedure.

TIS laws exogenously shifted the fraction f upwards by a certain percentage, and they would have, *ceteris paribus*, mechanically increased the expected sentence actually served $E[S^S|arrest]$ by that same percentage. However, the probability of conviction and the sentence upon conviction are determined endogenously, and as a result, $E[S^S|arrest]$ may have increased by less than the mechanical change. We estimate how the variables that are determined inside the courtroom, p , S^C, and S^A, respond to a change in f. (We unfortunately cannot estimate the effect of the TIS laws on $E[S^S|arrest]$since the data on prison releases do not cover enough years after the adoption of the laws.)

The predicted effect of the TIS laws on the probability of conviction follows a well-known model by Andreoni (1991). As the sentence actually served in prison increases, the social cost of convicting an innocent defendant also increases. The judge or jury who cares about the social costs of wrongful conviction then requires a higher standard of proof to convict a defendant.[9] The conviction rate among the cases resolved at trial should therefore fall. A similar trade-off may operate at other stages of the criminal procedure, such as the decision whether to dismiss a case.

In the plea bargaining process, changes in case outcomes reflect behavioral responses of the prosecutor (the terms of the plea bargain he offers) and the defendant (willingness to accept the terms). The predicted effects also depend on a particular model of the prosecutor, where the existing literature offers two broad views: According to one, the prosecutors are maximizing a well-defined deterrence objective, such as the total punishment imposed.[10] According to another, they pursue broader objectives of justice and fairness and apply punishment in accordance with these objectives.[11] Even though some predictions are ambiguous, certain observed effects of the TIS laws allow us to discriminate between these alternative views. A reduction in the plea rate is predicted by the "maximizing" view of the prosecutors, while an increase is possible under both views. A decrease in the probability that the prosecutor reduces charges is predicted by the "maximizing" view and an increase by the "justice-pursuing" view.

In the "maximizing" models of the prosecutorial behavior, the prosecutor typically offers a sentence that makes the defendant indifferent between accepting the plea or going

[9]Ezra and Wickelgren (2005) reach the same prediction in an alternative model where the population of defendants is endogenous.

[10]Landes (1971), Easterbrook (1983), and Reinganum (1988, 2000).

[11]Miceli 1996.

to trial.[12] If the TIS law applies irrespective of whether the defendant pleads guilty or is convicted at trial, the sentence to be actually served S^S rises mechanically as f increases for both trial and plea convictions. The prosecutor then need not adjust the imposed sentence S^C to make the defendant indifferent.[13] However, pleading guilty frequently implies being convicted of less severe charges compared to a potential conviction at trial. In such situations, the TIS laws may apply under the trial conviction but need not apply under the plea conviction. A maximizing prosecutor should then offer a longer sentence S^C or be less likely to reduce the charges. The prosecutor essentially "exploits" the increased gap between the actual sentence served under trial and under the plea and offers the defendant less favorable terms in the plea bargain.

The predicted impact on the defendants' plea choice is theoretically ambiguous. On the one hand, they would be more likely to plead guilty if the TIS law applies only to the trial sentence. However, if the prosecutors offer tougher bargains because of the TIS laws, the plea rate may fall. Likewise, the defendants would be less likely to accept the plea if they take into account that the probability of conviction at trial decreases.

In the "justice-pursuing" view of the prosecutors, the prosecutors may regard the increase in f as a departure from the prevailing norms of justice and use their discretion to mitigate its impact. They would then offer a shorter sentence S^C and be more likely to reduce charges. As a result, the defendants should be more likely to accept plea bargains.

In the sentencing stage, the judges may offset a higher fraction of the sentence actually served in prison simply by imposing shorter sentences. This would be particularly the case if they regard the mandated increase in the fraction of the sentence served as unjust.[14]

The preceding discussion of the particular behavioral responses implies predictions for the sign of our summary measures. The overall probability p that an arrested offender is convicted (by pleading guilty or at trial) is expected most likely to fall, although there is a theoretical possibility that it could rise if the prosecutors are mitigating the increased

[12]If the offenders are of different types (e.g., when they have imperfect information about the strength of evidence against them) and the prosecutor cannot distinguish their type, the optimal sentence offered involves only a marginal defendant being indifferent between the plea and trial: While defendants who think the case against them is weak strictly prefer a trial, those who think the case against them is strong strictly prefer pleading guilty.

[13]Whether he would optimally adjust the offered sentence upward or downward depends on the details of the model. For example, the very basic version of the Landes (1971) model with risk-neutral defendants and positive costs of trial predicts that the prosecutor should reduce the maximum sentence offered.

[14]The legal literature has been concerned with the sentencing implications of parole releases (see Genego, Goldberger, and Jackson [1975] for an early example). The empirical evidence on the relationship between sentences imposed by judges and the anticipation that the offender will be released early is, to our best knowledge, missing.

actual sentences and defendants become sufficiently more likely to accept plea bargains. The expected imposed sentence conditional on arrest S^A should most likely decrease as the probability of conviction decreases and the judges also reduce the sentences; however, there is a theoretical possibility that it may rise if the prosecutors offer sufficiently harsher sentences in plea bargaining.

2.3 Data and empirical strategy

We use the *State Court Processing Statistics: Felony Defendants in Large Urban Counties (SCPS),* an individual-level data set on approximately 100,000 criminal cases in state courts.[15] The sample covers 45 counties selected from 75 percent of the most populous counties in the United States. It tracks cases that were filed in May of every even year from 1990 to 2002. The universe of the data set is cases initiated by a felony arrest.[16] Due to missing values for relevant variables in some observations, the sample used in regressions has over 83,000 observations.

The SCPS data set contains rich information on each case: offender characteristics such as age, sex, and detailed prior record, information about the procedural aspects of the case (pretrial detention, type of attorney), and the final disposition of the cases including the length of the maximum jail or prison sentence, if applicable. The offenses are divided into 16 categories: violent crimes (murder, rape, robbery, assault, and other violent crimes) and non-violent crimes (burglary, larceny-theft, motor vehicle theft, fraud, other property crime, drug sales, other drug crimes, and four other minor categories). The data are summarized in the first column of Table 2.2.

The empirical strategy is based on a "quasi natural experiment", which compares the treatment cases (those covered by the TIS laws) with appropriately chosen control cases. We adopt two alternative "difference-in-differences-in-differences" (D-i-D-i-D) estimators, formally stated as

$$Y_{icst} = f(TIS_{icst}, TISstate_{st}, X_{icst}, \lambda_{ct}, \lambda_{av}, \epsilon_{icst}), \quad (2.3)$$

$$Y_{icst} = f(TIS_{icst}, TISstate_{st} \times violent_{icst}, X_{icst}, \lambda_{ct}, \lambda_{av}, \epsilon_{icst}), \quad (2.4)$$

[15]The data are collected by the Bureau of Justice Statistics. ICPSR study #2038.
[16]About 15 % of cases end up adjudicated as misdemeanors.

where i, c, s, and t denote the individual case, offense type, state, and year, respectively. Additionally, a denotes county and v denotes violent crime. Y_{icst} stands for the outcome variable, and $TIS_{icst}$is a dummy variable indicating whether the individual case is covered by the TIS law.[17] $TISstate_{st}$ is a dummy variable equal to one if a state has the TIS law in force. $TISstate_{st} \times violent_{icst}$ is a dummy variable equal to one if a state has adopted the TIS laws and a given offense is a violent felony. X_{icst} is a vector of individual characteristics of the offender and the case.[18] Finally, we include offense-year fixed effects λ_{ct} and county-violent crime fixed effects λ_{av}.[19] The offense-year fixed effects control for unobserved heterogeneity at the level of each offense and year. Compared to commonly used offense and year fixed effects, they impose less restrictive assumptions on the structure of the unobservables and allow, for example, separate national trends in the outcomes of criminal cases for each offense. The county-violent crime fixed effects control for unobserved heterogeneity at the county level, further disaggregated for violent and non-violent crimes. In alternative specifications, we include state-offense fixed effects instead.[20] ϵ_{icst} is an error term.

We use the D-i-D-i-D estimator, as opposed to the more conventional difference-in-differences (D-i-D) estimator since the identifying assumption for the latter is unlikely to hold. It would require that there is no differential change between the adopting and non-adopting states in the unobservables that affect outcomes in the offenses covered by the TIS laws after the adopting states implemented them. However, the states adopting the TIS laws may have adopted other "tough on crime" policies precisely because the objective of the laws is to punish certain crimes more severely.If that is the case, the error term may be correlated with the TIS_{icst} case dummy variable.

Our first specification (equation 2.3) therefore includes a TIS state control (variable

[17]The TIS case dummy may change for a given case during the criminal process. For example, the person may be arrested for a violent felony, and if convicted for a violent felony, the TIS law would apply. However, he may be convicted for a misdemeanor, and the TIS law would no longer apply. In the regressions, we set the TIS law according to the offense type that the offender is charged with at the relevant stage of the criminal process.

[18]Prior felony convictions (measured by dummies for 1, 2, and 3 or more prior convictions), number of prior misdemeanor convictions, log age, log age interacted with the prior conviction dummies, gender dummy, race/origin dummies (white non-hispanic, black non-hispanic, hispanic, and other), and type of attorney (public, private, assigned, *pro se*, and others) are included in the X vector.

[19]Represented by the interactions of county dummies with a dummy variable equal to one for violent offense and zero for other offenses.

[20]Ideally, we would include the county-offense fixed effects. However, there are too few observations for many county-offense combinations which prevent a meaningful estimation. The county-violent crime fixed effects or state-offense fixed effects are therefore workable compromises, still superior to a specification with only county or state fixed effects which assumes away any differences in unobserved heterogeneity between offense types within states.

$TISstate_{st}$). It captures the effect of state-specific unobservable variables that are potentially correlated with the adoption of the TIS laws and affect all crimes equally. The effect of the TIS laws is estimated from a within-state comparison of the change in the outcome for the crimes covered by the TIS laws with the crimes that are not covered. It is identified under the assumption that *within a state* the unobservable characteristics of TIS offenses and other offenses follow the same trend, even though they may not follow the same trend in the adopting and non-adopting states. In other words, the adopting states may have gotten "tougher on crime" than the non-adopting states, but then did so equally for all crimes.

The second specification (equation 2.4) exploits the fact that violent felonies are covered by the TIS laws in all states that adopted them while property, drug, and other non-violent crimes are covered only in some states. It includes a TIS state–violent crime interaction (variable $TISstate_{st} \times violent_{icst}$,) which captures the effect of unobservables that are correlated with the adoption of the TIS laws and affect violent crimes only. The effect of the TIS laws is estimated from a between-state comparison of the change in the outcome for non-violent crimes in the states that imposed the TIS requirement on both violent and non-violent crimes with the states that imposed the TIS laws on violent crimes only. The estimates are identified under the assumption the adopting states may have gotten "tougher" on violent than on non-violent crimes but must have gotten proportionately tougher on violent crimes irrespective of whether they imposed the TIS laws on all crimes or just violent crimes.[21]

A possible change in the sample composition poses a concern. The TIS laws have been accompanied by more intensive policing (Shepherd 2002). As the police arrests a larger fraction of offenders, it is possible that it also arrests a different sample of offenders; namely, the marginal offenders now being apprehended are likely to be those who are more difficult to identify. The evidence against such offenders is likely to be weaker, and they are less likely to be convicted. As a result, the average probability of conviction may fall even in the absence of any behavioral response. The importance of this problem can be checked by comparing the observable characteristics of cases before and after the adoption of the TIS laws; presumably, should there be a change in the sample composition of observables, it is quite likely that the unobservables changed as well. Table 2.2 show the

[21] Admittedly, the estimates are not identified if states imposed the TIS laws on certain crimes and targeted other "tough on crime" policies on the same crimes. Unfortunately, there is no case-level variation within a particular crime (which would be the case if the TIS laws applied only to offenders with certain characteristics, for example).

sample means for the observable characteristics of cases in the last year in the SCPS data set before the TIS laws were adopted and in the first year after the adoption.[22] The table does not show discernible changes in the observable characteristics. The only exception is the share of defendants who use a public defender, which rose by 10 percentage points in violent and by 11 percentage points in non-violent crime cases. This may indeed reflect a change in the strength of evidence, but the bias would rather go against the predicted effects (public defenders tending to represent in less defensible cases). We further address the sample composition issue in two robustness checks (section 2.4.7) with little effect on the results.

2.4 Results

This section presents the results in two steps: First, we present the summary measures: the reduction in overall probability of conviction conditional on arrest and the decrease in the length of sentence imposed given the arrest. Then we investigate specific channels behind the two summary findings[23] and the heterogeneity of behavioral responses across different offense categories.

2.4.1 Probability of conviction conditional on arrest

Our first summary measure of the effects of the TIS laws is the change in the probability that an arrested offender is eventually convicted, irrespective of whether via plea bargaining or conviction at trial. The marginal effects from probit estimates are presented in Table 2.3. They imply a reduction in the probability of conviction by 9 percent.

[22] The data set records arrests made in May of an even year. For the two states that adopted the TIS laws in the first few months of an even year, we use the observations two years after the adoption to allow the effect of TIS laws to be fully realized for the purpose of this before-after comparison.

[23] Two of the specific channels (the probability of conviction at trial and the length of sentence upon conviction)) are estimated on sub-samples of cases at different stages of the criminal procedure. The natural concern is that results for those channels are possibly affected by sample selection. The TIS laws may have changed the distribution of unobservable characteristics in cases that result in conviction or that proceed to trial. For example, if the TIS laws reduce the fraction of cases settled in plea bargaining, the marginal offenders now proceeding to trial would face longer potential sentences than the average offender previously proceeding to trial. Unfortunately, we do not have instruments that would be correlated with the likelihood that the case proceeds to the subsequent stage and at the same time would not be correlated with the error term in the outcome equation in that stage. We still think it is preferable to present such results as tentative evidence and interpret them with caution. The majority of the channels (the probability that the case is dismissed, the probability of pleading guilty, and the probability that the prosecutor reduces charges) are estimated on the full sample and hence are not affected by sample selection.

This result is robust to alternative specifications–controlling for the TIS state or the TIS state–violent crime interaction (columns 1 and 2) or for replacing the county-violent crime fixed effects with state-offense fixed effects (columns 3 and 4).[24] In all specifications, the marginal effects of the TIS case dummy are significant at the 1 percent level.

We also report the marginal effects of the TIS state and the TIS state–violent crime controls to demonstrate the appropriateness of the D-i-D-i-D estimator.[25] The coefficients of these two controls imply that the introduction of the TIS laws was associated with an overall increase in the probability of conviction, including the cases that were not subject to the TIS laws, on the order of 4 to 11 percent. Correspondingly, our estimates are different from the simple D-i-D estimates; when we exclude the $TISstate_{st}$ or the $TISstate_{st} \times violent_{icst}$ controls such that the specification is reduced to D-i-D, the marginal effect of the TIS_{icst} dummy becomes smaller in magnitude (-0.069). Even though these regressions do not directly estimate the choices by judges and juries, they nevertheless provide strong support for Andreoni's prediction in the sense that the criminal justice system convicts less if the sentences to be actually served are raised.

2.4.2 Sentence imposed conditional on arrest

The second summary measure of the behavioral responses to the TIS laws is the change in the sentence imposed conditional on arrest S^A. It is obtained by estimating equations 2.3 and 2.4 on the full sample of arrests, the dependent variable being the logarithm of the maximum prison or jail sentence imposed (in months). If the defendant was not convicted, the sentence in the regressions is set to zero.[26]

We estimate Tobit and quantile regressions instead of the conventional OLS for several reasons. The observed sentences are naturally censored at zero. They should also be censored at a very high sentence length since the requirement to serve 85 percent out of a 70-year maximum sentence may be of little practical significance. We therefore run Tobit regressions with the lower bound set at zero and the upper bound at 55 years.[27] Also,

[24] We also estimated alternative specifications which included a dummy variable for the presence of sentencing guidelines in a state and its interaction with the TIS case dummy; the key findings of the effects of the TIS laws were unaffected.

[25] The marginal effects on the two controls are 0.041 and 0.07 in the specification with county-violent crime fixed effects, and 0.1 and 0.11 in the specification with the state-offense fixed effects.

[26] The sentence is set to zero if the defendant was convicted but was punished with a fine instead of a prison or jail sentence. To deal with the logarithm of zero, we add one month to each sentence.

[27] As an alternative, we estimated the Tobit model with the lower bound equal to 4.5 months—treating non-convictions and convictions with short sentences as equivalent outcomes, with little effect on the results.

we expect the impact of the TIS laws to be more pronounced the longer the potential sentence is since the difference between serving, say 5 weeks or 8.5 weeks out of a 10-week maximum sentence may not be of such a concern to the judge than the difference between serving, say 5 years or 8.5 years out of a 10-year maximum sentence. The natural tool to address this issue is a quantile regression estimated at several quantiles. It predicts a change in a given quantile of the distribution of the dependant variable due to a change in the independent variable.

Table 2.4 shows the Tobit estimates. In the specifications with the offense-year and county-violent crime fixed effects, the marginal effect of the TIS case dummy is -0.114 when the TIS state control is included (column 1) and -0.097 when the TIS state-violent crime control is included (column 2). Both are significant at the1 percent level. In the specifications with offense-year and state-offense fixed effects, the marginal effects are smaller in magnitude (-0.083 and -0.039 for the respective controls, columns 3 and 4, and significant at the level of 1 and 10 percent).[28]

The estimates of the quantile regressions for the 75th and 90th quantiles are shown in Table 2.5.[29] They demonstrate that the behavioral response leading to shorter expected sentences is concentrated on the longest sentences, conditional on other factors. The marginal effects of the TIS case dummy are several times smaller in magnitude at the 75th quantile (columns 1 and 3) than at the 90th quantile although all of them are statistically significant at 1 percent level.

Both sets of regressions show fairly consistently that offenders covered by the TIS laws experience a reduction in the sentence that they can expect at the time of arrest compared to offenders not covered. The reduction was not trivial; we regard the average of the four Tobit estimates (8.3 percent) as the most preferred "summary" result.

2.4.3 Probability of conviction disentangled

The TIS laws may have reduced the likelihood of eventual conviction through three channels: a lower probability of conviction at trial, a higher probability that the case is dismissed before reaching a verdict on merits, or a lower probability that the offender

[28]The marginal effects of the TIS state and TIS state–violent crime interaction controls are positive as expected and significant at the 1 percent level. The unobserved factors that they capture increased the expected sentence by between 10 to 23 percent, depending on the specification.

[29]The quantile regressions are estimated at the 75th and 90th percentiles only. They could not be estimated at lower quantiles since zero sentence represents most observations for the 50th or lower quantiles, leaving almost no variation in the dependant variable.

accepts a plea bargain. The first two columns of Table 2.6 estimate the effect of the TIS laws on the probability of conviction at trial. They show a statistically significant reduction (by 9.8 percent) in the specification with the TIS state control and smaller and insignificant (5.2 percent) reduction in the specification with the TIS state-violent crime interaction.[30]

Columns 3 and 4 of Table 2.6 estimate the magnitude of the second channel by probit regressions with a dependant variable equal to one if the case was dismissed. The marginal effects of the TIS case dummy are 0.051 and 0.035 in the two basic specifications, and both are significant at the 1 percent level.[31] The tendency to convict less apparently applies to other stages of adjudication and not just to conviction/acquittal verdicts at trial. Unfortunately, we cannot say to what extent the higher probability of a dismissal is due to more dismissals by the judges during the pre-trial reviews and preliminary hearings or by the prosecutors since both are theoretically plausible.

2.4.4 Plea bargaining

The next set of probit regressions estimates the effect of the TIS laws on the likelihood that the case outcome is a guilty plea (columns 5 and 6). The estimates show a 9.5 percent reduction in the specification with the TIS state control and an 11 percent reduction in the specification with the TIS state–violent crime interaction.

The reduction in guilty pleas did not come about mechanically due to the fact that more cases were dismissed and therefore fewer cases were left to be potentially resolved through plea bargaining. When the regressions are re-estimated on a subsample of cases that were resolved either through plea bargaining or at trial, the marginal effects of the TIS case dummy are statistically significant at the 1 percent level although somewhat smaller in magnitude (-4.1 and -7.2 percent in the two alternative specifications).[32]

As the data do not record the exact terms that the defendants were offered in the plea bargaining process, we can only partially infer whether the reduced probability of

[30]The results have to be interpreted with caution since the trial cases consist of a highly selected sample. The selection, however, rather induces an upward bias. As the TIS laws induce fewer cases to be resolved through plea bargaining, the marginal defendants who would have plead guilty now proceed to trial. However, the evidence against such defendants would be stronger than the average defendants who proceed to trial, implying an increase in the probability of conviction. The relatively small sample size (4363 cases) inevitably limits the statistical significance of the results.

[31]The coefficients on the TIS state and TIS state-violent crime interaction controls are negative, again indicating a presence of other "tough on crime" factors that tended to reduce dismissals.

[32]Detailed results are available upon request.

accepting a plea bargain is due to the defendants being less willing to plead guilty holding the terms of the plea bargain constant or due to the prosecutors offering relatively worse terms. The SCPS data allow us to check two channels through which the prosecutors can make the bargains less generous: by being less likely to reduce the charge from felony to misdemeanor (while all defendants in the data set were initially arrested with a felony charge) or by being less likely to reduce the charge to a felony which carries a shorter sentence. Results from a probit dependant variable equal to one if the case was adjudicated as a misdemeanor (columns 1 and 2) of Table 2.7 show a significant reduction in the likelihood that the charges would be reduced to a misdemeanor (by 4 or 2.7 percent, respectively, depending on the controls). The next two columns report marginal effects from probit regressions where the dependant variable is equal to one if the predicted sentence for the offense for which the case was adjudicated is shorter than the predicted sentence for the offense for which the defendant was arrested.[33] The sample is restricted to cases that were adjudicated as felonies (to isolate the reductions to a misdemeanor which we already estimated) and that resulted in conviction since only for conviction cases is the adjudication offense recorded in the SCPS data set. The results show a reduction in the likelihood of reducing charges by 2.3 percent when the TIS state control is included and a smaller (and insignificant) reduction when the TIS state–violent crime control is included.

These findings are qualitatively similar to Kessler and Piehl (1998) and tend to support the "maximizing" view of the prosecutors as opposed to the "justice-pursuing" view of the prosecutors. The prosecutors appear to have "exploited" the increase in the severity of punishment by the TIS laws by offering the defendants harsher terms which they, in turn, became less likely to accept. The contrast to Bjerk's (2005) finding that the prosecutors got "softer" in response to the three-strikes laws warrants further discussion. The difference in results can hardly be attributed to the differences in empirical methodology as Bjerk (2005) adopts a very similar D-i-D-i-D empirical strategy, uses the same data, but estimates the prosecutors' response to a different punishment-enhancing policy. We

[33]The dependant variable was constructed as follows: First, we regressed the logarithm of the sentence as a function of offense dummies, year dummies, and county-violent crime dummies in a sample of cases that resulted in a conviction via plea bargaining. Second, we use the coefficients from this regression to predict, for each case in the sample, the sentence for which the defendant was arrested and the sentence for which the case was adjudicated. Third, if the latter predicted sentence is shorter than the former, the variable categorizing whether charges were reduced is equal to one. Across the sample, 11 percent of defendants who are convicted of a felony are convicted of a felony with a shorter sentence than for which they were arrested.

instead hypothesize that the responses of prosecutors (and other enforcement agents in general) to enhanced legislated sentences are inevitably context-specific. If prosecutors regard more severe sentences as unjust, the tendency to "pursue justice" would dominate, and their actions would mitigate the increased severity. On the other hand, if more severe sentences conform to the prosecutors' norms of justice (in a given context), the desire to mitigate is absent, and we observe responses consistent with narrow maximization objectives. The prosecutors apparently shared the objectives of the TIS legislation (Shepherd, 2002), which possibly explains why their observed responses are consistent with the prosecutorial maximization in the context of the TIS laws but not in other contexts.

2.4.5 Length of sentence imposed upon conviction

The last two columns of Table 2.6 show the effects of the TIS laws in the last stage of the criminal procedure, i.e., the sentencing of the defendants who were convicted.[34] Additional control variables are introduced: The plea dummy captures the difference between the sentence in plea and trial cases while its interaction with the TIS case dummy allows us to see whether the TIS laws had a differential impact on sentencing in plea cases vis-à-vis the trial cases. The marginal effects of the TIS case dummy are positive and significant at the 1 percent level (0.223 and 0.260). The marginal effects of the plea-TIS interactions are negative but small and insignificant, -0.053 and -0.058, implying that the TIS laws did not have a discernibly differential effect on the sentence length in cases resolved through plea bargaining or trial. The positive coefficient on the TIS case dummy was obtained also when we experimented with alternative specifications.[35]

These results do not support the prediction that the judges would mitigate a higher fraction of the sentence served by imposing shorter sentences.[36] One explanation is that our TIS case dummy is still partially correlated with other "tough on crime" policies even after controlling for the presence of the TIS law in the state, and the resulting upward bias is greater than the behavioral response. The second explanation comes from

[34] The Tobit regressions are equivalent to those estimating the sentence conditional on arrest except that we add a dummy variable for whether the defendant pleaded guilty and an interaction of the plea dummy with the TIS case dummy.

[35] Such as including dummy variables for the presence of sentencing guidelines in the state, their interaction with the TIS case dummy, or including state-offense fixed effects instead of county-violent crime fixed effects.

[36] The only rather weak indicators of the offsetting behavior are the offense-specific effects of the TIS laws (Table 2.8). For violent crimes, there is indeed a large and negative effect on the sentence length.

sample selection for which we were unable to correct. As the cases covered by the TIS laws are more likely to be dismissed, the relatively weaker cases that would have received relatively shorter sentences drop out of the sample. Also, defendants covered by the TIS laws are more likely to reject the plea bargain and go to trial. All else equal (including a sentence received if pleading guilty), the marginal defendant who was indifferent between a guilty plea and a trial expects to receive a longer sentence at trial than an inframarginal defendant who strictly prefers going to trial. If the TIS laws shift the marginal defendant to choose going to trial, the average sentence at trial would then rise, and the average sentence in plea bargains would fall, as the results suggest.

2.4.6 Offense-specific effects

We also estimate the impacts of the TIS laws specific to individual crime categories: murder, violent crime (other than murder), property, drug, and other crime.[37] Table 2.8 reports the main results from regressions that are equivalent to those in Tables 2.3-2.7, except that the single TIS dummy variable is replaced by interactions of the TIS dummy with the dummies indicating the five offense categories.[38]

The TIS laws affected the two main outcomes of interest, the probability of conviction conditional on arrest and the sentence imposed conditional on arrest, predominantly among non-violent crimes. The probability of conviction declined by 13.6, 6.9, and 14.5 percent for property, drug, and other crimes, respectively; the sentence conditional on arrest declined by 15.3, 9.9, and 14.3 percent. The estimated effects are significant at the 1 percent level. For violent crimes (other than murder), the results indicate a smaller (5 percent) reduction in the probability of conviction but no significant effect on the sentence imposed conditional on arrest. Almost no estimates are significant for murder.

Similar patterns apply to the particular channels behind the summary measures. The estimated effects of the TIS laws on the increase in the probability that a case is dismissed, the reduction in the probability that the defendant accepts the plea bargain, and the reduction in the probability that charges are reduced to misdemeanor are all larger in magnitude and have smaller standard errors for non-violent crimes than for the violent

[37]The "violent crime" (other than murder) category includes rape, robbery, assault, and other violent crime; the "property crime" category includes burglary, larceny-theft, motor vehicle theft, forgery, fraud, and other property crime; the "drug crime" category includes drug sales and other drug offenses; the "other crime" category includes weapons-related offenses, driving-related offenses, and other offenses.

[38]It is impossible to estimate the specification with the $TISstate_{st} \times violent_{icst}$ interaction variable because all states that adopted the TIS laws covered all violent crimes. The effects on violent crimes overall and sub-categories of violent crimes cannot be separated.

crimes. On the contrary, the estimates for the sentence imposed upon conviction show large reductions in the sentence for violent crimes but are not significant and have different signs for other crimes.

2.4.7 Robustness checks

Our main results are generally robust to alternative specifications. The first set of robustness checks addresses the concern that the TIS laws altered the distribution of the unobserved characteristics of arrests. If the police make more arrests and the marginal arrests tend to be cases with weaker evidence than the average cases, the probability of conviction would fall. This mechanism may explain the observed increase in the probability that the case is dismissed as the judges and prosecutors "weed out" some of the marginal arrests with particularly weak evidence. If, however, the judges and prosecutors apply the same standard for dismissing the case, the distribution of the strength of evidence in the sub-sample of cases that proceed beyond dismissal should remain constant. Our first robustness check exploits this plausible assumption by re-estimating the model on a subsample of cases that were not dismissed.[39] The estimated marginal effects of the TIS cases dummy on the probability of conviction are -0.05 and -0.059, depending on the specification (columns 1 and 2 of Table 2.9). They are somewhat smaller than the estimates obtained from the full sample[40] but remain highly statistically significant. Interestingly, the effect of the TIS state and TIS state–violent controls vanish. Likewise for the sentence conditional on arrest, the marginal effects of the TIS case dummy are somewhat smaller than the full sample estimates (-0.095 and -0.082), but they are not different in the statistical sense.

The second robustness check exploits information about the pretrial phase of the case. The defendant is more likely to be released on bail, and the terms of the pre-trial release tend to be more favorable if the evidence is weak or the case is less serious. Should the judges apply the same standards in the pre-trial release decisions under the TIS laws as they did before, the information about pre-trial release is a relevant control for the strength and seriousness of the cases. The SCPS data contain information about the type of pre-trial release granted,[41] the amount of bail set, and the behavior of the defendant

[39] As a result, the sample is reduced to approximately 62,000 observations.

[40] The confidence intervals of the marginal effects obtained from the full sample do not overlap with the confidence intervals of the marginal effects obtained from the sample excluding the dismissed cases.

[41] The types of pretrial release are categorized as follows: financial release, nonfinancial release, emergency release, held on bail, denied bail, release conditions unknown, detained but reasons unknown.

during the pre-trial phase.[42] In columns 5-8, we re-estimate the model with dummy variables for each release type, the amount of bail set, and a dummy variable equal to one if the defendant failed to appear.[43] Including these controls has essentially no effect on the estimates in the probability of conviction regressions. In the sentence conditional on arrest regressions, the marginal effect of the TIS case dummy is the same (0.114) when the TIS state control is included and slightly smaller (0.077) when the TIS state x violent crime interaction is included.

The third robustness check addresses the concern that the TIS state and the TIS state–violent crime control may not adequately capture the unobservables affecting the outcomes of violent crimes. We therefore estimate the model on a sub-sample of non-violent crimes only, reducing the estimator to a simple D-i-D. It comes at a cost of dropping the crimes for which the TIS laws were designed but at a benefit of keeping the crimes for which any confounding effects are likely to be less serious. The estimated effects (-0.098 for the probability of conviction and -0.129 for the sentence conditional on arrest) are similar to those obtained in the full sample and to the offense-specific effects reported for non-violent crimes in Table 2.8.

The last set of checks exploits the variation in the intensity of the TIS laws. There are two sources of such variation. First, while most states followed the federal law and required offenders to serve 85 percent of the sentence, 3 states in our sample opted for 100 percent[44] and 2 states for 50 percent only.[45] Second, the fraction of the time actually served had varied among states and offenses prior to the adoption of the TIS laws. We expect the TIS laws to "bite" more if the offenders had previously served a shorter fraction of the sentence. We ran the same set of regressions, where we replaced the TIS dummy variable (and all interactions) with a continuous variable equal to the predicted fraction of the sentence served.

The predicted fraction is constructed as follows: For cases not covered by the TIS laws, it is computed from the National Corrections Reporting Program (NCRP) data series, individual-level data on approximately 2.9 million prisoners released from prison between 1989 and 2002.[46] The data were collected at the time of release and contain information on the individual characteristics of prisoners, the offense for which they were

[42] Whether he failed to appear, became a fugitive, or was re-arrested.
[43] The failure to appear is likely a good indicator of strength of the evidence and eventual conviction.
[44] Georgia, Pennsylvania, and Virginia.
[45] Indiana, Maryland.
[46] The data is available at http://www.icpsr.umich.edu/cocoon/ICPSR/SERIES/00038.xml.

sentenced, the maximum and minimum sentence to which they were sentenced and the time served under the current admission. The predicted fraction of the sentence served is calculated by dividing the time served by the maximum sentence for each offender and then taking the average for each state-year-offense combination. The information about the time of admission to prison allows us to distinguish which prisoners were sentenced under the TIS laws and which were not. The number of observations for some states[47] is too small to predict the fraction for each state-year-offense. These states were dropped, reducing the number of observations used in the regressions by 7 percent. For cases covered by the TIS laws, we set the predicted fraction to the minimum fraction required by the TIS legislation in the respective state for the respective offense.[48]

The results are presented in Table 2.10.[49] They are qualitatively and quantitatively similar for the following outcomes of interest: probability of conviction conditional on arrest, probability of conviction at trial, and the probability of reducing charges to a misdemeanor. For example, the marginal effect of the predicted fraction on the probability of conviction conditional on arrest is -0.074, which implies approximately a 2.5 percent reduction in that probability.[50] The marginal effect on the probability of conviction at trial implies a 12 percent reduction in that probability.

Qualitatively the same but quantitatively different estimates are found for the probability of a guilty plea—the effect is also negative but very small and statistically insignificant. For three outcomes the specification with the expected fraction implies qualitatively different results than the TIS dummy: The effects on the sentence conditional on arrest and the probability that the case would be dismissed are statistically insignificant and have the opposite sign. The effect on the sentence imposed upon conviction is negative,

[47] Arizona, Connecticut, the District of Columbia, Indiana, and Pennsylvania.

[48] Ideally, we would like to use the predicted fraction served for cases covered by the TIS laws as well. However, we have two reasons why we prefer the legislated rather than predicted fraction. First, the predicted fraction is likely to be downward-biased for the cases covered by the TIS laws. New admissions to prison covered by the TIS laws occur only after the TIS laws are in force (1994 or later in most states). The NCRP data set therefore cannot record releases of prisoners who served 8 or more years post-TIS (and actually more than mere 2 years for those admitted to prison in 2000). Missing observations for releases after 2002 induces a downward bias in the estimate of the fraction since we are more likely to observe prisoners who were released early. Due to this limitation we are also unable to observe post-TIS fraction of the sentence served for very long maximum sentences. Second, it may be more plausible to assume that agents in the criminal process acted upon the expectation that the post-TIS offenders would serve the legislated minimum fraction rather than the ex-post realizations of the fraction.

[49] Due to space limitations, only the coefficients on the expected fraction served and their standard errors are reported. Full results are available upon request.

[50] The TIS laws raised the expected fraction of the sentence served from approximately 50% to 85%, i.e., by approximately 0.35. The coefficients on the fraction served should therefore be divided by 1/0.35 (approximately 3) to obtain estimates comparable to those on the TIS dummy variable.

statistically significant, and large in magnitude. The last result is at least consistent with the theoretical prediction that judges should respond to the TIS laws by imposing shorter sentences, which was not confirmed in the main regressions (Table 2.6).

2.5 Conclusion

Our evaluation of the impacts of the Truth-in-Sentencing laws produced consistent evidence on several channels of behavioral responses to more severe punishment in the criminal justice process. Requiring offenders to serve a higher fraction of their sentence in prison significantly reduced the probability that an arrested offender is convicted. This result represents one of the first empirical tests of the popular Andreoni (1991) model. Moreover, the magnitude of the reduction (9 percent) is empirically relevant and suggests that this line of behavioral response should be seriously considered in the design of sentencing policies.

The overall effect of the TIS laws was a reduction in the imposed sentence expected upon arrest. The stated intention of the TIS laws to increase criminal punishment was therefore mitigated by the behavioral responses on several margins. The magnitude of the mitigating effect is empirically relevant as well. In the absence of the behavioral responses, the increase in the fraction of the sentence served to 85 percent would have increased the expected sentence actually served by 70 percent on average. The behavioral responses reduced the expected imposed sentence conditional on arrest by 8 percent, which implies that the expected sentence actually served rose by "only" 56 percent.[51] The behavioral responses have therefore undone about one-fifth of the intended direct effect of the TIS laws. Also, they inevitably increased the disparities in punishment. Because of the TIS laws, a higher fraction of defendants walk away with no punishment at all while a smaller fraction of those who are convicted are punished much more severely.

Last, the results give an interesting perspective on the behavioral responses of the judges and prosecutors. The behavioral responses were most pronounced for non-violent crimes but small or insignificant for violent crimes. The primary goal of the TIS laws was to punish violent offenders more heavily. If the judges and prosecutors share that goal,

[51] The expected sentence actually served was $pS^C \cdot 0.5 = S^A \cdot 0.5$ in the absence of the TIS laws (0.5 being the average fraction of the sentence served). In the absence of behavioral responses, it would rise to $S^A \cdot 0.85$, a 70-percent increase. The behavioral responses reduced S^A by 8 percent. Hence the new sentence actually served, conditional on arrest, increased to $S^A \cdot 0.92 \cdot 0.85$, which is 56 percent higher than the pre-TIS law level.

they may not apply any offsetting behavior in violent crime cases, but they may have as well regarded the TIS laws as unnecessarily overreaching when they were applied to non-violent crimes. Tthe offsetting behavior is then a logical reaction. A similar conclusion can be drawn when comparing our finding that the prosecutor got "tougher" in plea bargaining in response to the TIS laws with Bjerk's (2005) finding that the prosecutors instead got "softer" in response to the three-strikes laws. Judges and prosecutors do respond to more severe sentences, but they do so selectively. Alternative models of judicial and prosecutorial behavior need not be, after all, mutually exclusive but may correctly characterize the behavior of even the same individual judges and prosecutors depending on the context of the particular legislation.

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Table 2.1: Adoption of the TIS laws

State	Year of introduction	Requirement(%)	Type of crime covered
Alabama	NA		
Arizona	1994	85	all
California	1994	85	violent felony
Connecticut	1996	85	violent felony
District of Columbia	1989	85	violent felony
Florida	1995	85	all
Georgia	1995	85	violent felony
Hawaii	NA		
Illinois	1995	85	all
Indiana	NA		
Kentucky	1998	85	violent felony
Massachusetts	NA		
Maryland	NA		
Michigan	1994	85	part I violent
Missouri	1994	85	repeat or dangerous felony
New Jersey	1997	85	violent felony
New York	1995	85	violent felony
Ohio	1996	85	felony
Pennsylvania	1911	100	part I violent
Tennessee	1995	85	violent felony
Texas	1993	50	aggravated
Utah	1985	85	all
Virginia	1995	100	felony
Washington	1990	85	part I violent
Wisconsin	1999	100	felony

Sources:
United States General Accounting Office: Truth In Sentencing: Availability of Federal Funds Influenced Laws in Some States, Report to Congressional Requesters, February 1998.
Chen, Elsa: Impact of Three Strikes and Truth in Sentencing on the Volume and Composition of Correctional Populations, Report Submitted to the National Institute of Justice, March 2000.
Table includes only the states covered in the SCPS data set.

Table 2.2: Summary Statistics

	Mean	violent crime		non-violent crime	
Case Outcomes	all	last year before TIS adoption	first year after TIS adoption	last year before TIS adoption	first year after TIS adoption
% convicted cases/arrest	67.31	64.24	60.06	75.59	72.33
	(46.90)	(47.94)	(48.99)	(42.96)	(44.74)
sentence/arrest in months	15.06	29.17	24.23	15.19	11.66
	(69.19)	(117.58)	(114.15)	(71.44)	(54.96)
% convicted cases/trial	80.23	77.01	75.25	76.30	78.59
	(39.83)	(42.19)	(43.26)	(42.62)	(41.08)
% dismissed or acquitted	25.71	32.01	36.62	18.03	22.30
	(43.70)	(46.66)	(48.19)	(38.44)	(41.63)
% pleaded guilty	63.01	58.24	53.80	73.48	68.96
	(48.28)	(49.33)	(49.87)	(44.15)	(46.27)
plea sentence/plea conviction	18.32	31.73	27.98	18.17	14.66
in months	(59.79)	(83.27)	(88.01)	(72.29)	(59.31)
trial sentence/trial conviction	82.32	178.36	149.08	87.40	46.29
in months	(229.83)	(369.52)	(354.35)	(228.13)	(123.49)
Individual Characteristics					
age	29.99	28.32	29.68	29.56	30.137
	(10.30)	(10.31)	(11.25)	(9.54)	(10.05)
% black	36.30	41.97	37.55	34.07	34.11
	(48.09)	(49.36)	(48.43)	(47.40)	(47.41)
% hispanic	21.07	21.40	22.26	21.81	21.65
	(40.78)	(41.02)	(41.61)	(41.30)	(41.19)
% women	16.72	10.99	13.10	16.41	18.07
	(37.31)	(31.28)	(33.75)	(37.04)	(38.49)
prior felony convictions	1.07	0.86	0.84	1.05	1.03
	(1.91)	(1.63)	(1.60)	(1.85)	(1.76)
prior misdemeanor convictions	1.61	1.45	1.50	1.75	1.67
	(2.58)	(2.53)	(2.51)	(2.76)	(2.67)
public defender (%)	40.35	40.17	53.04	42.37	54.83
	(49.06)	(49.04)	(49.92)	(49.42)	(49.77)
private attorney (%)	13.12	14.74	12.26	14.11	13.17
	(33.77)	(35.46)	(32.81)	(34.82)	(33.81)
assigned attorney (%)	11.09	11.87	13.94	12.22	10.80
	(31.40)	(32.34)	(34.65)	(32.75)	(31.04)
# Observations/arrest	83506	2402	2381	7628	7937
# Observations/ trial	4482	187	198	211	341
# Observations/trial conviction	3567	144	146	161	267
# Observations/ plea conviction	52387	1395	1281	5578	5470

Standard errors in parentheses.
Only states that eventually adopted the TIS laws are included in the summary statistics for a comparison between before and after TIS. To calculate the overall means of the variables, additional states that did not introduce TIS (Alabama, Indiana, Hawaii, Massachusetts, Maryland, and Texas) are also included.

Table 2.3: Probit Estimates, Probability of Conviction Conditional on Arrest

	1	2	3	4
TIS case	-0.094***	-0.088***	-0.093***	-0.061***
	(0.010)	(0.010)	(0.010)	(0.009)
TISstate	0.042***		0.105***	
	(0.011)		(0.010)	
TISstate x violent		0.070***		0.108***
		(0.017)		(0.015)
offense x year dummies	Yes	Yes	Yes	Yes
county x violent dummies	Yes	Yes	No	No
state x offense dummies	No	No	Yes	Yes
# observations	83,506	83,506	83,437	83,437
pseudo R^2	0.153	0.153	0.140	0.139

* significant at 10%; ** significant at 5%; *** significant at 1%
Marginal effects on the probability and their standard errors (in parentheses) are reported.
All regressions include the individual characteristics of the offender and the case (age, sex, race, prior convictions, and type of attorneys).

Table 2.4: Tobit Estimates, Imposed Sentence Conditional on Arrest (all cases)

	1	2	3	4
TIS case	-0.114***	-0.097***	-0.083***	-0.040
	(0.026)	(0.025)	(0.026)	(0.025)
TISstate	0.106***		0.185***	
	(0.028)		(0.032)	
TISstate x violent		0.172***		0.233***
		(0.058)		(0.061)
offense x year dummies	Yes	Yes	Yes	Yes
county x violent dummies	Yes	Yes	No	No
state x offense dummies	No	No	Yes	Yes
# observations	83,244	83,244	83,244	83,244
pseudo R^2	0.095	0.095	0.093	0.093

* significant at 10%; ** significant at 5%; *** significant at 1%
Marginal effects on the sentence and their standard errors (in parentheses) are reported.
All regressions include the individual characteristics of the offender and the case (age, sex, race, prior convictions, and types of attorneys).

Table 2.5: Quantile Estimates, Imposed Sentence Conditional on Arrest

	1	2	3	4
TIS case	-0.111***	-0.0161***	-0.394***	-0.183***
	(0.000)	(0.000)	(0.045)	(0.046)
TISstate	0.421***		0.513***	
	(0.000)		(0.048)	
TISstate x violent		0.258***		0.215**
		(0.000)		(0.097)
offense x year dummies	Yes	Yes	Yes	Yes
county x violent dummies	Yes	Yes	Yes	Yes
quantile	75%	75%	90%	90%
# observations	83,244	83,244	83,244	83,244
pseudo R^2	0.236	0.236	0.194	0.193

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%
The reported coefficients denote the marginal effects on the probability.
All regressions include the individual characteristics of the offender and the case (age, sex, race, prior convictions, and types of attorneys).

Table 2.6: Probablity of Specific Case Outcomes and Length of Sentence upon Conviction

	1	2	3	4	5	6	7	8
Dependent Variable	Conviction at trial		Dismissed		Plea guilty		Sentence upon conviction	
	Probit		Probit		Probit		Tobit	
TIS case	-0.098**	-0.052	0.051***	0.036***	-0.095***	-0.110***	0.223***	0.260***
	(0.049)	(0.044)	(0.009)	(0.009)	(0.011)	(0.010)	(0.071)	(0.072)
TISstate	0.075**		-0.048***		0.005		0.025	
	(0.038)		(0.009)		(0.011)		(0.034)	
TISstate x violent		0.035		-0.044***		0.071***		-0.133*
		(0.051)		(0.015)		(0.018)		(0.079)
Plea							-0.379***	-0.379***
							(0.034)	(0.034)
Plea x TIS case							-0.053	-0.059
							(0.063)	(0.063)
county x violent dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
offense x year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	4,363	4,363	83,506	83,506	83,506	83,506	55,954	55,954
pseudo R^2	0.185	0.184	0.166	0.166	0.129	0.129	0.112	0.112

* significant at 10%; ** significant at 5%; *** significant at 1%
Marginal effects and standard errors (in parentheses) are reported.
All regressions include the individual characteristics of the offender and the case (age, sex, race, prior convictions, and type of attorneys).

Table 2.7: Probit Estimates, Probability of Reducing Charges

	1	2	3	4
Dependent Variable	Misdemeanor		Felony with shorter sentence	
TIS case	-0.040***	-0.027***	-0.023***	-0.011
	(0.006)	(0.005)	(0.008)	(0.008)
TIS state	0.030***		0.018**	
	(0.007)		(0.009)	
TISstate x violent		0.011		-0.011
		(0.013)		(0.015)
offense x year dummies	Yes	Yes	Yes	Yes
county x violent dummies	Yes	Yes	Yes	Yes
# observations	83,245	83,245	36,851	36,851
pseudo R^2	0.194	0.194	0.118	0.118

* significant at 10%; ** significant at 5%; *** significant at 1%
Marginal effects on the probability and standard errors (in parentheses) are reported.
All regressions include the individual characteristics of the offender and the case (age, sex, race, prior convictions, and type of attorneys).

Table 2.8: Offense-Specific Effects

Dependent Variable	Sample	Offense Categories				
		murder	other violent	property	drug	other
Probability of conviction	all	0.066 (0.057)	-0.050** (0.020)	-0.136*** (0.014)	-0.070*** (0.013)	-0.145*** (0.020)
Expected imposed sentence	all	0.138 (0.177)	-0.027 (0.054)	-0.153*** (0.030)	-0.100*** (0.029)	-0.144*** (0.041)
Maximum sentence imposed	convicted	0.449* (0.241)	-0.580** (0.262)	0.041 (0.129)	-0.087 (0.155)	0.289* (0.164)
Probability of conviction	trial	0.114*** (0.042)	-0.114 (0.074)	-0.190** (0.080)	-0.049 (0.065)	-0.031 (0.082)
Probability of a guilty plea	all	-0.009 (0.067)	-0.023 (0.021)	-0.139*** (0.014)	-0.071*** (0.013)	-0.157*** (0.020)
Probability of dismissed	all	-0.045 (0.051)	0.036* (0.019)	0.065*** (0.012)	0.047*** (0.012)	0.060*** (0.017)
Probability of reducing charges	all	-0.012 (0.070)	-0.043*** (0.010)	-0.029*** (0.006)	-0.047*** (0.005)	-0.028*** (0.009)

* significant at 10%; ** significant at 5%; *** significant at 1%
Marginal effects and their standard errors (in parentheses) are reported.
All regressions include the individual characteristics of the offender and the case (age, sex, race, prior convictions, and type of attorneys), offense-year dummies, county dummies interacted with violent crime dummies, and the interaction term of the TIS dummy and each crime category type.

Table 2.9: Robustness Checks

	1	2	3	4	5	6	7	8	9	10
	Dismissed cases excluded				Pre-trial covariates included				Non-violent crimes only	
	Length of Sentence/arrest		Conviction/arrest		Length of Sentence/arrest		Conviction/arrest		Sentence	Conviction
TIS case	-0.096***	-0.082***	-0.050***	-0.060***	-0.115***	-0.077***	-0.092***	-0.083***	-0.126***	-0.098***
	(0.033)	(0.032)	(0.007)	(0.007)	(0.025)	(0.024)	(0.011)	(0.010)	(0.025)	(0.011)
TISstate	0.081**		0.000		0.148***		0.048***		0.088***	0.029***
	(0.035)		(0.004)		(0.027)		(0.011)		(0.028)	(0.011)
TISstate x violent		0.129*		0.017***		0.173***		0.070***		
		(0.072)		(0.005)		(0.056)		(0.017)		
offense x year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
county x violent dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	61,773	61,773	61,231	61,231	81,796	81,796	82,053	82,053	62,572	62,767

* significant at 10%; ** significant at 5%; *** significant at 1%

Marginal effects and standard errors (in parentheses) are reported.

All regressions include the individual characteristics of the offender and the case (age, sex, race, prior convictions, and type of attorneys).

Table 2.10: Estimates of the TIS Effect Using the Predicted Fraction of the Sentence Served

Dependent Variable	Sample	Regression	Specification	
			TISstate	TISstate x violent
Probability of conviction	all cases	probit	-0.075***	-0.078***
			(0.021)	(0.021)
Expected imposed sentence	all cases	tobit	0.098	0.110*
			(0.060)	(0.060)
Expected imposed sentence	convicted cases	tobit	-0.297*	-0.298*
			(0.161)	(0.158)
Probability of conviction	trial cases	probit	-0.360***	-0.285***
			(0.090)	(0.083)
Probability of a guilty plea	all cases	probit	-0.003	-0.033
			(0.022)	(0.022)
Probability of dismissal	all cases	probit	-0.027	-0.036*
			(0.019)	(0.0190)
Probability of reducing charges	all cases	probit	-0.059***	-0.049***
to misdemeanor			(0.015)	(0.015)

* significant at 10%; ** significant at 5%; *** significant at 1%
The table reports the marginal effect and standard errors (in parenthese) on the fraction of the predicted sentence served in regressions that are equivalent to regressions in Tables 2.3 through 2.7 except that the TIS case dummy is replaced with the fraction of the expected sentence served.
Specification "TISstate" denotes regressions controlling for the presence of the TIS law in the state (equation 2.3). Specification "TIS state x violent" denotes regressions controlling for an interaction of the TIS state dummy and a violent crime dummy (equation 2.4).
All regressions include the individual characteristics of the offender and the case (age, sex, race, prior convictions, and type of attorneys), offense-year dummies, and county dummies interacted with violent crime dummies.

Chapter 3

Air Pollutants in the Czech Republic - Decomposition Analysis

Fusako Tsuchimoto and Milan Scasny

Abstract

We statistically decompose the change in the emission level of the various pollutants such as SOx, CO, NOx, VOC, and particulate matters (PM) in the Czech Republic. First, we decompose the emission level in 1995 - 2007 into three factors: emission intensity effect, scale effect, and composition effect. We find that the implementation of command and control types of law, which required the large sources of emissions to satisfy emission limits until 1999, were highly effective in the reduction of the emission level of SOx, NOx, CO, and PM. Moreover, the reduction was mainly induced by a change in the emission intensity effect, which captures the change in environmental efficiency relative to the per capita GDP.

Secondly, we further decompose the emission intensity effect into three factors (1)a fuel intensity effect (2)a fuel mix effect, and (3)an emission coefficient effect. We find that the emission coefficient effect is the most prominent factor, especially during the period of 1995-1999. In other words, command and control regulation motivates firms to decrease their emission levels by improving abatement technology, represented by the end-of-pipe technology, not by changing fuel usage.

Keywords: Air Pollution, Environmental Kuznets Curve hypothesis, Decomposition Analysis

JEL Codes: Q53, Q58, O13

3.1 Introduction

Many argue that rapid economic growth is accompanied by a change in environmental quality. One of the most prominent hypothesis, Environmental Kuznets Curve hypothesis, (EKC hypothesis) claims that per capita GDP and environmental quality have a negative relationship in the early stage of the development of a country. In the later stage, after a certain threshold, the economic growth, in contrast, has a positive effect on the environmental quality. Grossman and Krueger (1995), in their pioneering study, which supports EKC hypothesis, show that there is an inverse-U or N relationship between some of the environmental degradation level indicators and per capita income. However, it is usually hard to base some policy recommendations on any reduced form analysis of environmental degradation and per capita income: We cannot tell through which channel the level of GDP per capita affects environmental quality nor can we estimate the extent each factor's contribution. Compared to the reduced-form analysis in the Environmental Kuznets Curve literature, where the only overall effect of the GDP level on pollution is measured, a decomposition analysis can identify through which channel the economy affects environmental quality and thus would help to induce clearer policy recommendations, as noted in Tsurumi and Managi (2010).

In this paper, we conduct a statistical decomposition analysis to examine the driving force of change in the air pollutants and the degree of their contribution to environmental degradation. Specifically, we analyze the emission level of various pollutants such as sulphur dioxide (SOx), carbon monoxide (CO), nitrogen oxide (NOx), volatile organic compounds (VOC), and particulate matters (PM) in the Czech Republic. First, the emission level of pollutants in 1997-2007 in the Czech Republic is decomposed into 3 factors: an emission intensity effect, a scale effect, and a composition effect. Emission intensity effect measures how the firms are environmentally efficient relative to their economic output. Scale effect measures how economic growth as a whole affects air pollutant emissions. Finally the composition effect captures how the change in economic structure affects pollution levels, e.g. a decrease in the output of a pollution-intensive sector leads to cleaner production, and thus the overall emission level would go down.

Further, our unique data set may enable us to conduct a more refined analysis than existing studies, which is the main contribution of this paper to the existing literature: We decompose intensity effect into three factors (1)a fuel intensity effect (2)a fuel mix effect, and (3)an emission coefficient effect. The fuel intensity effect measures a change in the consumption composition of consumption of each type of fuel used in the production per unit of economic output. The fuel mix effect measures how the composition of various types of fuels used affects emission levels. Finally, the emission coefficient effect measures how effectively fuels are used in terms of air pollutants, i.e., it captures the change in end-of-pipe type technology.[1] In the existing literature, the emission coefficient is usually time invariant, which is a theoretically determined value from chemistry. In our data, the exact amount of pollutants released by a particular type of fuel is reported, e.g. how much SO_2 is released per tonne of hard coal at each facility level. That means that compared to the conventional time invariant or sectoral level emission coefficient, we have richer variation at facility level as well as in time dimension. Only few studies, such as Viguier (1999) or Ang and Pandyan (1997) use a time variant emission coefficient. However, they use the sectoral level emission coefficient, which means that their method would give a biased result unless those firms in the sample exactly represent the entire sector in terms of emission level, which is quite a strong assumption. Further, in our data set, both emission amounts and fuel consumption are directly measured, which leads to richer variation compared to knowing the value of one variable only and then calculating the other using the theoretical value.

In this paper, specifically the following questions are answered: (1) What is the contributing factor to the relationship between per capita income and environmental degradation in the Czech Republic during the period between 1995-2007? (2) What is the extent and trend of the contribution of each factor?

First, the finding of this paper is the law in the Czech Republic, which was implemented in 1991 with further specifications introduced in 1997 and which required large sources to satisfy a certain emission limit by 1999, was quite effective in reducing the emission levels of SOx, NOx, CO and PM: it contributed to a significant decrease in the emission of these pollutants in the period 1995-1999. Secondly, we find that the leading factor of this decrease was the intensity effect, which is consistent with the findings of other studies from developed or transition countries.

Separating the contribution of the emission coefficient from the fuel mix allows us to observe the behavioral response of the firms to environmental policy targets. When the emission coefficient is the prominent contributor to the change in emissions, it suggests

[1] Here 'end-of-pipe type technology' refers to all the abatement technology which reduces emission amounts given the same amount of fuel consumed. Representative of such technology would be an installed filter or improvement in environmental efficiency of the combustion process.

firms adjust their environmental behavior by improving their environmental technology. On the other hand, if the fuel mix effect is the main contributor, it shows that the firm becomes environmentally efficient by changing the composition of the fuels they use in their production process. At last, the large intensity effect suggests that firms decrease the use of their fuels per unit of economic output to reduce the overall emission level.

In fact, the second finding of this paper is that the reduction of the air pollutants in the Czech Republic between 1997-1999 was mainly due to the emission coefficient effect. This finding shows that command and control regulation did not motivate firms to simply decrease their usage of the fuel amount or change the composition of the fuels used but motivated firms to decrease their emission levels by improving on their end-of-pipe type technology, even though the firms used the same amount of fuel.

Thirdly, we find that after 2000, after satisfying EU regulation requirements, firms did not have the motivation to decrease their emission levels further, so the emission level of pollutants stays more or less stable. Further, the structure of the economy in the Czech Republic actually contributes to an increase in the emission level.

The paper is structured in the following way. In the next part, the institutional background of air emission and regulation in the Czech Republic and the related literature are presented in accordance with our analysis. In the second and third section, the methodology and information on data are presented. The result of the analysis is presented in the fourth section, and the conclusions and remarks on a future perspective of the research follow.

3.1.1 Institutional Background

A decomposition analysis has been employed by many studies to investigate the factors which contribute to the emissions of air pollutants. Most of the studies target Western European countries (Torvanger 1991, Lofgren and Muller 2010, and many others), and there are only very few studies that examine cases in transition countries. In this sense, our study fills this gap as it examines the factors that contribute to changes in emissions in the Czech Republic, a CEE country, during 1995-2007, which includes its transition and post-transition period.

Our analysis focuses on the period of economic and political transformation in the Czech Republic that started after the Velvet Revolution in 1989. During the communistic regime, the centrally planned system was characterized by the high energy, resource, and pollution intensities due to a lack of environmental regulation. By looking at the high emission level of pollutants, one can see that there was an excessive amount at the beginning of the 1990s. However, this high level of environmental degradation did not persist: the Czech government introduced several policies to decrease the emission level of pollution in order to comply with the Community Acquis of the EU. As a result, the emission amount of airborne pollutants significantly decreased in the Czech Republic by 1999. Specifically, the new Air Quality Law No.309/1991, which required each existing large stationary emission source (power plants, and industrial processes) to comply to strict emission levels until 1998, and this contributed to the large reduction of air pollutants.[2]

These emission limits determined in 1991 were amended in 1992 and 1995. Further amendments were made by new decrees in 1997 and 2002. To sum up, command and control regulation was effective in the Czech Republic in reducing the large amount of emissions of air pollutants, especially SO_2, NOx, and PM. In contract, using a market-based instrument, such as emission permits trading after 1990, was neither effective nor efficient in regulating air quality in the Czech Republic.[3]

3.1.2 Literature Review

Environmental Kuznets Curve (EKC) hypothesis states that there is an inverted-U curve relationship between per capita income and the emission level of various pollutants. Starting with the pioneering work done by Grossman and Krueger (1995), there are numerous studies discussing validity of this hypothesis: Some empirically show or disverify the hypothsis.

For example, Stern, Common and Barbier (1996) critically review the literature on EKC hypothesis in terms of the data and econometric method used in the studies. Further they conduct a simulation using the estimated parameter from the literature and conclude that SOx (SO_2) should continue to rise with the development level of a country rather than decline as the EKC hypothesis suggests.

Agras and Chapman (1999) estimate a dynamic EKC relationship between income and CO_2 or per capita consumption of energy, including energy prices, based on the stylized

[2]No. 309/1991 applies at the federal level (Czechoslovakia). On the other hand, No.389/1991 applies to the national level (the Czech Republic). Furthermore, No.309 is more substantial and determines the emission limits and deadlines to fulfill the requirement; On the other hand, No.389 is administrative and gives the competence to CIZP (Česká inspekce životního prostředí - Czech environment inspectorate).

[3]For a detailed discussion regarding the market-based instrument in the Czech Republic, see Maca, Melichar and Scasny (2010).

fact that the total global emission of CO_2 increases or decreases with a change in oil price. Specifically, as in Suri and Chapman (1998), they include the ratio of imports and exports of all manufactured goods over domestic production to capture the openness of the economy. They find that there would be no evidence for an EKC relationship between income and energy consumption if energy prices and trade variables are controlled for in the estimation. In this regard, actually their result leads to the criticism of EKC: (1)The countries' emission moves from SOx or other pollutants towards CO_2 emission as countries become more opened. (2) However, the mobility of the pollutants depends on their prices rather than onthe development level of the country.

Most studies estimate a reduced form equation because of data availability or the difficulty in finding an appropriate identification strategy. Because of the nature of reduced form analysis, the reason why per capita income and emission levels have (or do not have) such a relationship is unclear in these studies. Further, Stern (2002) finds that the results from the decomposition model have better statistical properties than the standard EKC specification and discusses that the basic EKC model is a nested version of a decomposition model, and the EKC model is the one with restrictions. In other words, his paper motivates the use of statistical decomposition in examining the emissions of air pollutants or energy use.

In fact, recently, a relative large number of studies employ a decomposition analysis to investigate the contributing factor of changes in airborne pollutants or energy use. These studies differ in various ways: the number of factors of the decompsition, the decomposition method employed, and the regions covered by the analysis.

First, there are differences in the decomposition method itself. The two main streams are the Laspeyres and Divisia index methods. The Laspeyres index has an advantage in that it is quite intuitive and easier to understand. However, when the absolute contribution of each factor is relatively large, it may generate large unexplained residuals. In this regard, the extension of classic Laspeyres methods, the Sun-Shapley method, can overcome this shortage and manage to achieve perfect decomposition (no residuals); however, their method allocates the residuals arbitrarily. Thus, some studies employ the Divisia index-based method in their analysis, which overcomes this problem (e.g. Viguier 1999; Ang 2004). In this regard, Viguier analyzes specifically SO_2, NOx, and CO_2 emissions in three CEE and former CIS countries (Hungary, Poland, and Russia) and three OECD countries, (the US, the UK and France) for the period between 1971-1994. First, he uses the energy-balance method to evaluate the emissions by sector and concludes that transition economies generally have a higher intensity of emission. Then, he proceeds to decompose energy intensities into 4 factors, namely (1) the emission factors, (2) the fuel mix, (3) the sectoral structure of energy consumption, and (4) the energy intensity. He concludes that the most significant determinant of emission in transition economies is energy intensity.

Secondly, the factors into which emissions are decomposed can differ across studies. For instance, Sun (1999) conducts a 4-factor decomposition analysis on the emission of carbon dioxide in the 24 OECD countries from 1960-1995. Specifically, he uses the Sun-Shapley index developed in Sun (1998), which is a modified version of the Lasperyrs index, which generates no residuals. He decomposes the change in the emissions into 4 effects (1)an emission coefficient of CO_2 following Torvanger (1991); (2)a structural change, (3)a scale effect, and (4)an intensity effect. Note that in his paper, the emission coefficient is time invariant which is derived from the theoretical value in chemistry. Similarly, the emission coefficients in the Viguier (1999) study are calculated based on the parameters of the substance content of fuels, the fraction of substance removed by pollution abatement, and fraction of substance retained in ash respectively. The choice of parameter value is based on the literature from the late 80s on data from the RAINS model (Amann 1990), and OECD/IEA statistics. This is a time variant measurement of emission coefficients, so in a sense, it is superior to Torvanger; however, as mentioned before, the emission amount is calculated using the emission factor, i.e., the variation comes only from the difference in the value of emission factors. In this paper, both the emission amount and the fuel amount used per pollutant are reported at facility level, and thus, it gives much richer variation in the analysis.

Third, the studies differ in how they use disaggregated data, whether they analyze annual changes or changes over a certain period, or whether they aggregate an analysis over several time periods. In this regard, Lofgren and Muller (2010) argue that the results from a decomposition analysis are sensitive to this choice, and decomposition analysis should be undertaken at the most disaggregated level possible to avoid biased results.

Fourth, regarding the geographical coverage, most studies investigate the former EU-15 countries and Asian countries, mainly China, with some studies focusing on the USA and Canada or selected OECD and IEA countries (see e.g. Lofgren and Muller 2010). Only few applications of a decomposition analysis in African countries or Central and Eastern European (CEE) countries exist, and in this respect, our study tries to fill this gap in the literature. One of the few studies which analyses the emission in CEE countries, is Viguier (1999). He analyzes the SO_2, NOx, and CO_2 emissions in three Eastern countries (Hungary, Poland, and Russia) and three OECD countries, (the U.S., the U.K., and France) from 1971-1994. He uses the so-called energy-balance method to evaluate the emissions by sector and finds that transition economies generally have a higher intensity of emission. Then he proceeds to decompose energy intensities into 4 categories: (1) emission factors[4] (2) fuel mix (3) structural change and (4) energy intensity. He concludes that the most significant determinant of emissions in transition economies is energy intensity, which is estimated using a bottom-up method. In our paper, it is obtained directly from the data. Later in this paper, we discuss the difference between our data set and that from Viguier.

Another work that deals with former CIS countries is Cherp, Kopteva, and Mnatsakanian (2003). They analyze the quality of air in Russia from 1990-1999, using a decomposition analysis. Specifically, they decompose the change in emission intensity into (1) change in the structure of the economy (a change in the share of sector) and (2)a change in the amount of the emission by each sector (change in the intensity by sector). He finds that the total air emission had decreased over the period mostly due to the decline in economic output. Basically, he claims that in terms of emission in Russia, there are two effects which go in the opposite direction. One is a structural effect which works positively on emission because the Russian economy invested in an industrialized sector and became pollution intensive. The other is the intensity effect which affects emissions negatively because the technology became more environmentally friendly. In fact, our paper shows that in the time period until 1999, the intensity effect was strongly negative as in study of Cerp et al. and after 2000, the structural effect has the most dominant and positive effect on the emission level in the Czech Republic.

Further Bruha and Scasny (2006) conduct a 3-factor decomposition analysis on the emissions in the Czech Republic for the period between 1992-2003. Our paper extend the time span of the data set to 2007 and conducts a deeper analysis using a more detailed data set. We are able to further decompose the level of emission into 5 factors using the facility level value directly obtained from the actual data.

[4]Emission factor is the same as the emission coefficient in this paper. Both terms refer to the same definition: the emission amount per particular type of fuel used.

3.2 Methodology

To measure the magnitude of the contribution of each factor to the emissions of certain pollutants over time, we conduct a decomposition analysis by aggregating pooled cross-sectional data at the firm level with sectoral level panel data.

3.2.1 Decomposition analysis

There are several ways to conduct decomposition analysis. According to Ang (2004), the method should be chosen such that it passes both the factor reversibility and time reversibility tests. Of these tests, the most important test is the factor reversibility. To pass the test of factor reversibility, it requires perfect decomposition, i.e., no residuals. In this regard, the conventional Laspeyres index is not recommended because it can create huge residuals, sometimes larger than the factors which should be analyzed.

The method used in Bruha and Scasny (2006) satisfies the critical points above, however, since their method is based on logarithmic approximation, their result is sensitive towards large magnitude of change (more than a 10 % changes creates large approximation errors).

Given these reasons, we use the logarithmic mean Divisia index (LMDI) method instead of the Laspeyres method, which satisfies the property of perfect decomposition and where additive and multiplicative linkages are clear. The total change can be decomposed multiplicatively:

$$E_{tot} = \frac{E^T}{E^0} = D_{x1} \cdot D_{x2} \cdot D_{x3} \cdots D_{xn} \cdot D_{resid},$$

where E is total magnitude of change in the emission, upper subscript denotes time, D_y is the contribution of factor y to the emission level, D_{resid} is that of the residual term, and $x_k, k = 1, ..., n$ is the factor into which the emission level of pollutants can be decomposed.[5] The effect of kth factor in multiplicative decomposition can be expressed by:

$$D_{x_k} = \exp(\sum \frac{L(E_i^T, E_i^0)}{L(E_T, E_0)} \ln(\frac{x_{k,i}^T}{x_{k,i}^0})),$$

where i denotes sectors, and $L(a, b)$ is the logarithmic average of the two numbers, a and b.[6]

[5] E.g., in a 3-factor analysis, k=1, ..., 3, and in a 5-factor, k=1, ..., 5.

[6] Specifically $L(a, b) = \frac{a-b}{\log a - \log b}$, if $a \neq b$,else $L(a, b) = a$.

On the other hand, in the additive decomposition, the emission level can be decomposed in the following way:

$$\begin{aligned} \widehat{E_{tot}} &= E^T - E^0 \\ &= \widehat{D_{x1}} + \widehat{D_{x2}} + \widehat{D_{x3}} + \cdots + \widehat{D_{xn}} + \widehat{D_{resid}}, \end{aligned}$$

where $\widehat{D_{xk}}$ denotes the contribution of kth factor to the change in emission from time 0 to T:

$$\widehat{D_{xk}} = \sum_i L(E_i^T, E_i^0) \ln(\frac{x_{k,i}^T}{x_{k,i}^0}),$$

The multiplicative and additive decomposition factors share the following properties.

$$\frac{\widehat{E_{tot}}}{\ln E_{tot}} = \frac{\widehat{D_{xk}}}{\ln D_{xk}}, \text{ for all } k.$$

In other words, unlike in the Laspeyres method, there is a clear linkage between additive and multiplicative decomposition in the LMDI method.[7] Further, as the magnitude of the total change becomes larger, the interpretation of the results becomes less intuitive with the multiplicative LMDI, and we mainly focus on the additive LMDI to ease the interpretation.

3.2.2 Three-factor analysis

The emission level of the pollutants can be decomposed into:

$$\Delta_t E = \sum_i (\Delta_t \frac{E_i}{Y_i} + \Delta_t \frac{Y_i}{Y}) + \Delta_t Y,$$

where i denotes sector, and t denotes time (year in this case). The operator $\mathbf{\Delta} X$ expresses the fraction of the change in the variable X from time $t-1$ to t. $\Delta_t E$ denotes the change in the emission. Y_i is the change in the gross value added (GVA) in sector i. Y is the sum of GVA across the sectors, i.e., the total output of the whole economy.

Thus, the first term captures the effect of the change in the emission intensity (intensity effect), the second term captures the effect of the change in the composition of

[7]For more discussion regarding the linkage, see Ang (2004).

economic activity (composition effect), and the third term captures, then, the effect of economic growth (scale effect).

3.2.3 Five-factor analysis

In addition to the emission level, our data set contains information on how much pollutants are emitted by each type of fuel: E_{ijt}, where j denotes the fuel type. Using the richer information described above, we conduct not only the conventional decomposition analysis described above, but also a five-factor analysis: (1)an emission coefficient effect (EC), (2)a fuel mix effect (FM), (3)a fuel intensity effect (FI), (4)a composition effect, and (5)a scale effect. In other words, we decompose the intensity effect further into three factors: fuel intensity, fuel mix effects, and emission coefficient effects. Specifically,

$$\Delta_t \frac{E_i}{Y_i} = \Delta_t \frac{E_{i,j}}{F_{i,j}} + \Delta_t \frac{F_{i,j}}{F_i} + \Delta_t \frac{F_i}{Y_i}.$$

In words, each factor measures:

EC ($\Delta_t \frac{E_{i,j}}{F_{i,j}}$) - the emission attributed to unit of fuel j [t/GJ]

FM ($\Delta_t \frac{F_{i,j}}{F_i}$) - the share of fuel j over the total fuel

FI ($\Delta_t \frac{F_i}{Y_i}$) - the fuel needed to produce a unit of output (GVA) [GJ/$GVA)]

We conduct the five-factor analysis for five categories of fuel: (1) Coal, (2) Bio wood and other solids, (3) Natural Gas, (4) Other gas, and (5) Liquid fuels. A more detailed categorization of the fuels is reported in Table3.1.

3.2.4 Zero Value Problems

Because of the logarithmic function in the equation, our analysis is sensitive to zero or negative values in the data set. In order to deal with this problem, following Ang (2004), we replace the negative or zero value with sufficiently small numbers,$10^{-10} - 10^{-20}$. Note that this replacement is valid only when the following conditions are not satisfied (Wood and Lenzen 2006):

(i) zero values outnumber non-zero values,

(ii) the data set contains many small values, and

(iii) the magnitude of changes is large.

Looking at the summary statics of our data set, fortunately we do not have the problem described; thus, we replace the negative or zero value with $10^{-10} - 10^{-20}$ as Ang suggests.[8]

3.3 Data

Our data set contains unique information on how much emission is produced by which type of fuel, e.g., how much SO_2 is emitted by the use of natural gas. This enables us to conduct a five-factor decomposition analysis as well as a three-factor analysis. The analysis is conducted over REZZO 1 firms, which are the main sources of emissions: large stationary sources of polluters whose thermal output is greater than 5 MW. First, we summarize our data sources, the way we compile the original data set into the data set which is used in the analysis in this paper, and then statistics of the compiled data.

3.3.1 Description of Data Set

The source of emission and energy data is the Air Pollution Emission Source Register (REZZO – Register emisí zdrojů znečištění ovzduší). Database is compiled by the Czech Hydro-Meteorological Institute and covers classical pollutants such as SO_2, NOx, CxHy (VOC), CO, and particulates matter (and other trace pollutants) as well as the consumption of more than 20 types of fuel per all emission sources. The REZZO database distinguishes four broad categories of emission sources in which data are stored: category Rezzo1 (R1) and R2 includes large and medium-sized emission sources, grouped by their thermal output amounts that are larger or smaller than 5MW respectively; R3 reports the emission released by local units, including households and area sources, while R4 reports emissions from mobile sources. In the case of large emission sources (R1), data are gathered at facility level. Data for medium-sized sources (R2) are reported at the firm level.

Having information about the firm and its associated sector allows us to collapse the environmental data at the sector level. To ensure the consistency with the economic variables, we collapse the environmental data into 60 sectors. The share of emissions released from the combustion processes of large stationary emission sources (R1comb) on

[8] If we encountered the problems described above, we would use the alternative methodology proposed by Wood and Lanzen (2006).

total aggregate emission is described in Figure 3.1. As can be seen, the emission of SOx and NOx from R1comb represent a large amount of total emissions, about 80% over the entire period. Regarding particulate matters, the share of R1comb decreased from 40% in 1995 to 16% in 2007 due to a strict abatement introduced in large sources.[9] Large combustion sources contribute to emission of CO and VOC by only a small amount, 5% to 8% or 6% to 14% respectively.

In REZZO, we can further divide the emissions attributable to stationary sources (R1 and R2 categories) into two broad categories. The first category covers the emission generated from the combustion of fuels, the second covers the emission generated from various kinds of technological processes. While our database on combustion processes allows us to derive emissions per fuel type used for each unit, the emissions from technological processes does not contain the information on the attribution of a specific fuel. That is why, in this paper, we particularly focus on the emission by R1 combustion process.

There are three possibilities for emission sources, which can generate emissions from fuel combustion. The homogenous unit describes a facility, which burns only one specific type of fuel, and as a matter of fact, all emissions can be directly attributed to this specific type of fuel. In some cases, however, the facility can use two types of energy, when the second type of fuel is used only in negligible amounts compared to the first one. For instance, natural gas can be used to fire up a coal-burning furnace. In such cases, we attribute all emissions to the first, the main type of fuel. In the case of burning more types of fuel (known as non-homogenous units), we attribute the respective emission for each type of fuel based on the technical information of each boiler used.

It should also be noted that the definition of CxHy changed before and after 2001: after 2001, methane is included though before 2001, it was not. Thus, we conduct our analysis separately for 2 periods. From the data set described above, we compute summary statistics for the emission level of the pollutants and the Gross Value Added (GVA) (see Figure 3.1). All values are nomalized to the value of the year 1995 (100). The GVA value is adjusted with respect to current price level, using the GDP deflator. By looking at the constant decline until 1999 (the complete obligation due date was December 31st, 1998), we can see that the law 117/1997 which limits the emission amount of all the basic

[9] Admittedly, our composition effect does not include the change in contribution of R1 to the emission of PM, and we should note that during the period 1995-1999 when the share of the R1comb on total emission of PM changes, the degree of the compositional effect can be negatively biased.

pollutants except for VOC seems to have been quite effective,

REZZO reports fuel consumption for 24 energy types overall, which we merge into five broader categories in our analysis as described in Table 3.1. In Figure 3.2, the trend of fuel from 1995 to 2007 is displayed. Overall, the total consumption of fuels by R1comb firms remained more or less at the same level over 1997-2007 except in the earlier years when fuels were used more. Coal share over total energy used is 80%. Natural gas and other gases contributed by about 15%, use of oils were declining from 5% to 2% of the total energy used. Contrary to oils, the consumption of biomass was increasing from 0.5% to about 1% in 2007. The consumption of the fuels is presented in Figure 3.2.

Consumption of other gas was partly substituted by the consumption of natural gas, i.e., the consumption of natural gas was increasing over the period, whereas that of the other gases decreased. Most of the emission factors for each type of fuel were decreasing, which indicates more efficient abatement. In Table 3.2, we also compare the emission coefficient for each major fuel type with the average emission factor as used in Viguier (1999) for three countries (Russia, Poland, and Hungary) in the year 1994. As can be seen, most of the Viguier values, except for the emission from natural gas, are much larger than the value derived from the REZZO database for the Czech Republic.

3.4 Results

In this section, we document the findings from our decomposition analysis. First, we present those of a 3-factor analysis and secondly, 5-factor analysis follows.

3.4.1 Three-factor analysis

The results of the three-factor analysis are presented in Figure3. 3-3.8 in the appendix. As mentioned above, since VOC changed its definition in our data set, we analyzed VOC for 2 separate periods, 1995-2001 and 2002-2007 (Figure 3.9& Figure 3.10). First of all, we can see that the law which requires large sources to decrease their emission levels of basic air pollutants until the end of 1998 and came into force in middle of 1997, was quite effective. All the pollutants except VOC, SOx, NOx, CO, and PM decrease from 1997 to 1999 significantly, and this downward trend suddenly diminishes in 2000. From this result, we can see that after satisfying the emission limit, the firms did not have the incentive to decrease emissions further, so the emission level since 2000 stays more or less constant. This is one of the concerns regarding command and control regulation: It will not motivate firms to decrease emissions further than the requirement. One reason is that as a country develops, the structure of its economy becomes less emission intensive, and thus, we should see a decreasing in the emission level with the higher development of the economy. However, our result shows that this is not the case in the Czech Republic in this period.

The results of all air pollutants show that the most important factor during the period 1995-1999, when the emission levels of the pollutants significantly decreased, is the intensity effect, which captures the contribution of the change in emission intensity over output of the economy. To see this intensity effect more closely, we continue to a 5-factor analysis, decomposing the intensity effect into 3 factors.

3.4.2 Five-factor analysis

In the three-factor decomposition of airborne emissions, we find that the intensity effect was negative with respect to the emissions of SO2, NOx, PM and CO, except for some years (e.g. 2000, 2001) over the entire period analyzed. In the five-factor analysis — whose results are presented in Figures 3.9-3.14 — the intensity effect is further decomposed into a fuel intensity effect, a fuel mix effect, and a emission coefficient effect in order to find the main driver of emission changes.

The first interesting finding is that the emission coefficient effect is negative for all the pollutants except for VOC until 1999, i.e., when the Air Quality Act required the fullfillment of the emission targets. It suggests that the firms focused their effort on satisfying the requirement by introducing or adjusting end-of-pipe technologies. In terms of NOx emission (Figure 3.13), the emission coefficient factor had a smaller effect than the other pollutants, such as SOx, and PM, due to the fact that it is more difficult to abate nitrogen emissions than other air pollutants. The emission of CxHy released by large stationary emission sources was not primarily targeted by the Air Quality Law (Decree 117/1997), and as a result, the emission coefficient did not play a significant role in changing their volume in the later period (2003-2007).

Second, the fuel intensity effect — measured by total GJ used in production per monetary unit of GVA —was negative after 2001 when the effect was mostly due to a relatively larger increase in economic output compared to energy use. The fuel intensity effect led to an increase in emissions particularly in two years, 1997 and 2000. This effect was mainly due to a decrease in the economic output of the power sector, which is particularly pollution-intensive (NACE 40) and some manufacturing sectors (NACE 26, 27) in those years. At the country level, the year 1997 is characterized by the largest decrease in economic output due to recession, while energy consumption in its aggregate increased in 2000 by the largest amount (9%). During 1995-2000, the fuel intensity effect was stable or was slightly increasing, which suggests that investment was aimed more at improving environmental technology in production processes than in saving energy, keeping the economic output at the same level. The interesting point is that the real price of energy largely increased in 1997, 2000, and 2005-06; however, relatively slow adjustments of the firms resulted in a larger negative fuel intensity effect in the years that followed (1999, 2002-03, or 2006 respectively).

The fuel mix effect was mostly negative in the case of particulate matters until 2000, which suggests changing the input towards environmentally friendly fuels.

3.4.3 A cumulative analysis of five factor decomposition

Table 3.3 reports a cumulative change in the emission levels and the decomposition of this change into five effects. During the entire period 1995-2007, the emission of PM, SOx and CO was reduced by 93%, 82%, and 69%; the emission of NOx was reduced lessk; however, still by 29% compared to the initial levels in 1995. In the case of PM, SOx, CO emissions, the emission coefficient effect led to their reductions most, while the composition effect is the strongest for NOx emission.

In Viguer (1999), the author decomposes the emissions of CO_2, SOx, and NOx in CEE countries during their transition period: an analysis is conducted in Hungary, Poland and the USSR during 1990-1994. The energy intensity (measured as an aggregate fuel consumption per unit of production at the country level) and fuel quality, (emissions per fuel type used on a given economic sector, i.e. emission coefficient) have the strongest effect on changes in emission intensities in the three analyzed Eastern European countries in Viguier (1999). Specifically, the energy intensity effect has a strong effect in Hungary and Poland, and the emission coefficient has a strong effect in the Czech Republic and the USSR. In other words, in the Czech Republic and the USSR, there was an improvement in abatement technology, and it contributed significantly to the reduction of the emissions of air pollutants during the period analyzed in both studies.

On the other hand, the energy intensity had a reverse direction on emissions than the emission coefficient had in three countries; it decreased the intensities in Hungary and Poland, but increased them in the USSR and the Czech Republic for some period. there was This shows investment activity in energy-saving technologies in Hungary and Poland during 1990-1994, which was not actually the case in the USSR nor in the Czech Republic. In this respect, the situation during 1995-1999 in the Czech Republic was more comparable with the situation in the USSR from 1990 to 1994. Admittedly, since our data generation process, methodology, and time period covered[10] are quite different from those of Viguier (1999), one might not be able to simply compare the results. However, we believe that the comparison of our study and similar studies conducted in transition countries would still give some policy implications.

3.5 Conclusion

In this paper, we analyze a driving force of an increase or decrease in the emission levels of various pollutants in the Czech Republic by using decomposition analysis. Using the unique data set we obtain, which contains information on the amount of emission per particular type of fuels, we manage to conduct a finer decomposition analysis than found in existing studies. We find that the law which required the large sources to satisfy emission limit till the end of 1998 was quite effective in reducing emissions: it motivated firms to improve upon their environmental efficiency, especially abatement technology, represented by and end-of-pipe technology and decreased emission amounts during the period 1995-1999 by using fuel efficiently in terms of emission.

After 2000, the emission levels of the pollutants stay more or less stable, which is quite intuitive if one considers the criticism over command-control environmental policies being "motivatively discouraging". Further, in some periods, change in structure of the economy in the Czech Republic actually contributed to an increase in emission levels, which is inconsistent with the other reasoning related to EKC hypothesis: as a country develops, the structure of the economy becomes less emission intensive, and thus, we see a downward trend in emission levels.

Decomposition analysis with a longer time span might give us more interesting results, considering the effect of the EU-ETS system implemented in 2005. Firms are expected to decrease the fuels consumed to reduce GHG emissions, and thus, instead of an emission

[10]Our decomposition analysis starts in 1995 when the Viguer analysis just ends (it covers the period of 1970 to 1994).

coefficient effect, fuel mix or fuel intensity might be prominent in the future. Further, we have to admit that the decomposition analysis usually does not prove causality, and in this respect a theoretical or empirical model should be constructed separately to support the decomposition analysis *ex-ante.*

3.6 References

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Figure 3.1: Emission of the air pollutants (R1combustion process), 1995-2007 in Czech Republic

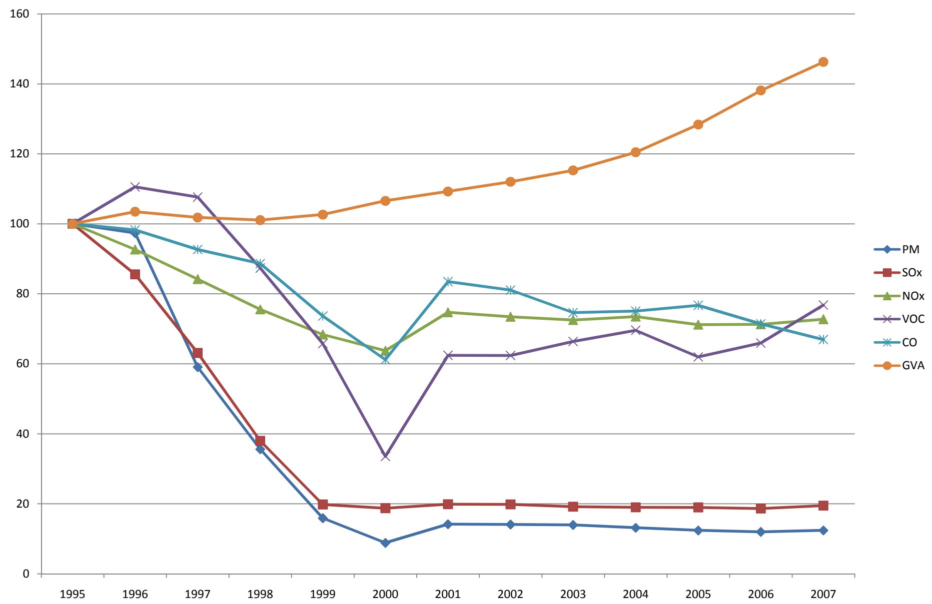

Figure 3.2: Fuel Consumption 1995-1999, in Czech Republic

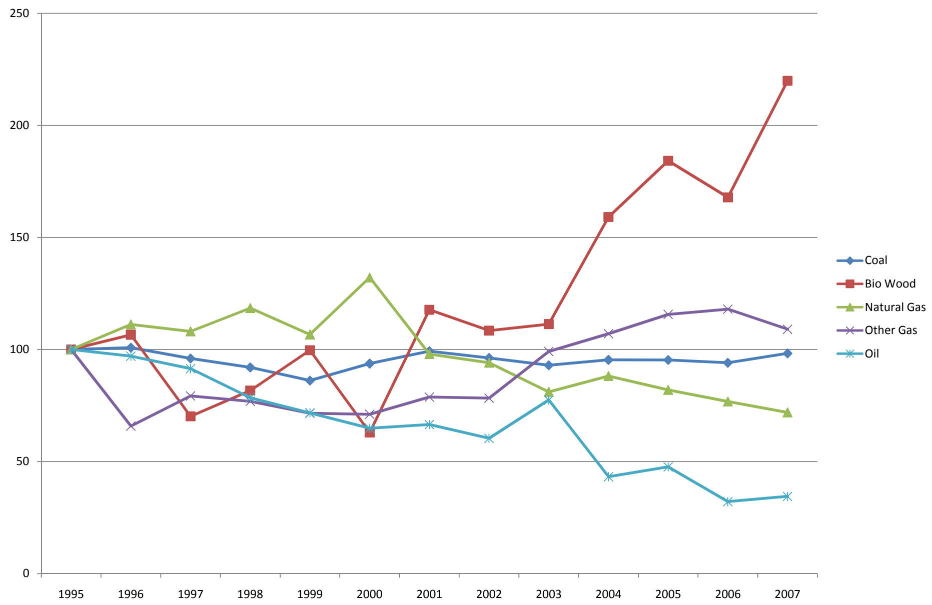

Figure 3.3: Composition of emission in terms of Rezzo

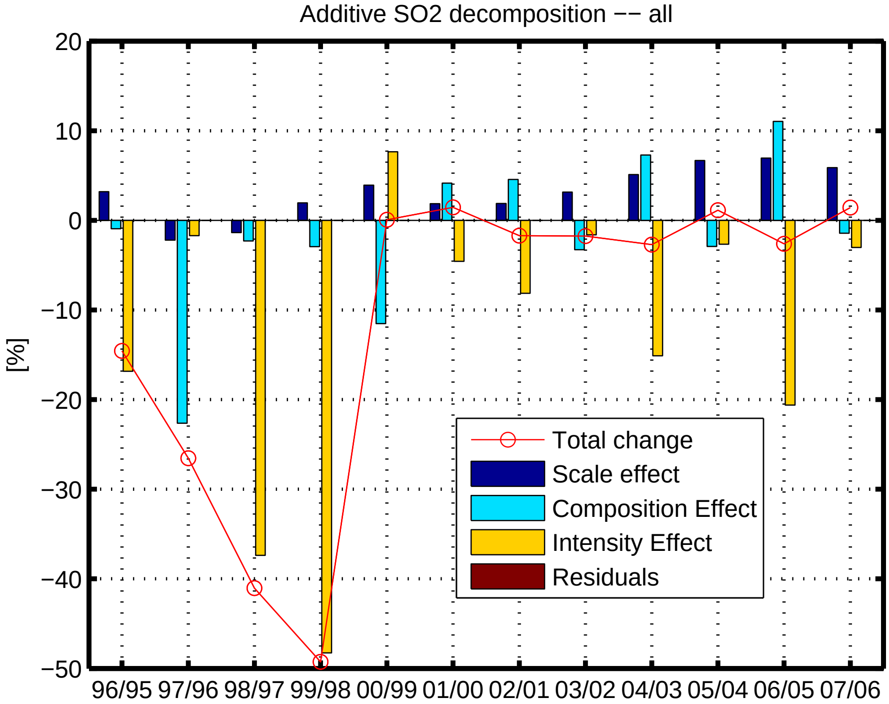

Figure 3.4: Fuel consumption share of Rezzo

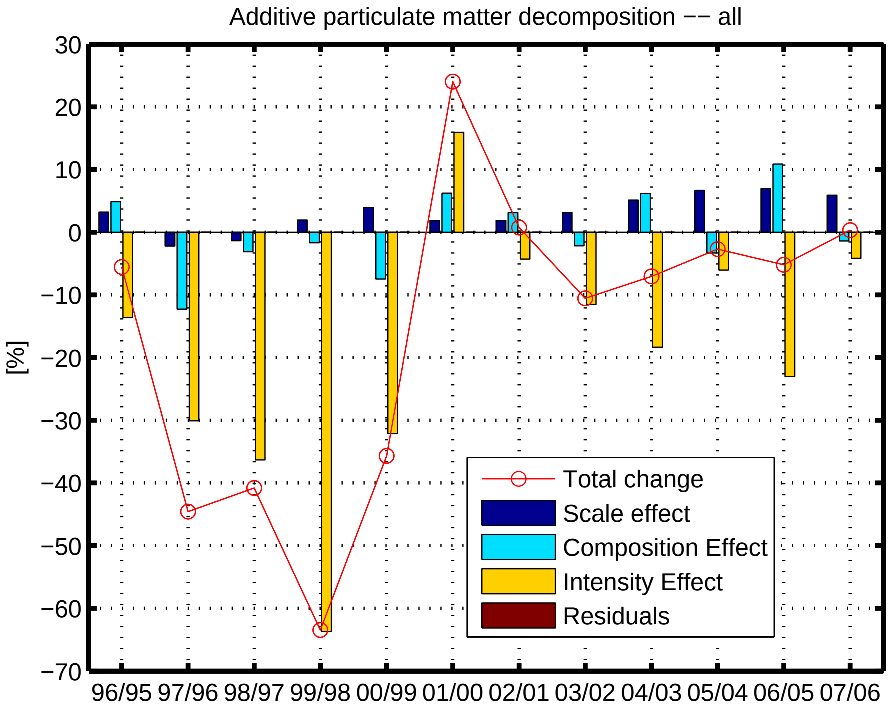

Figure 3.5: 3 factor decomposition (SO_2), 1995 - 2007

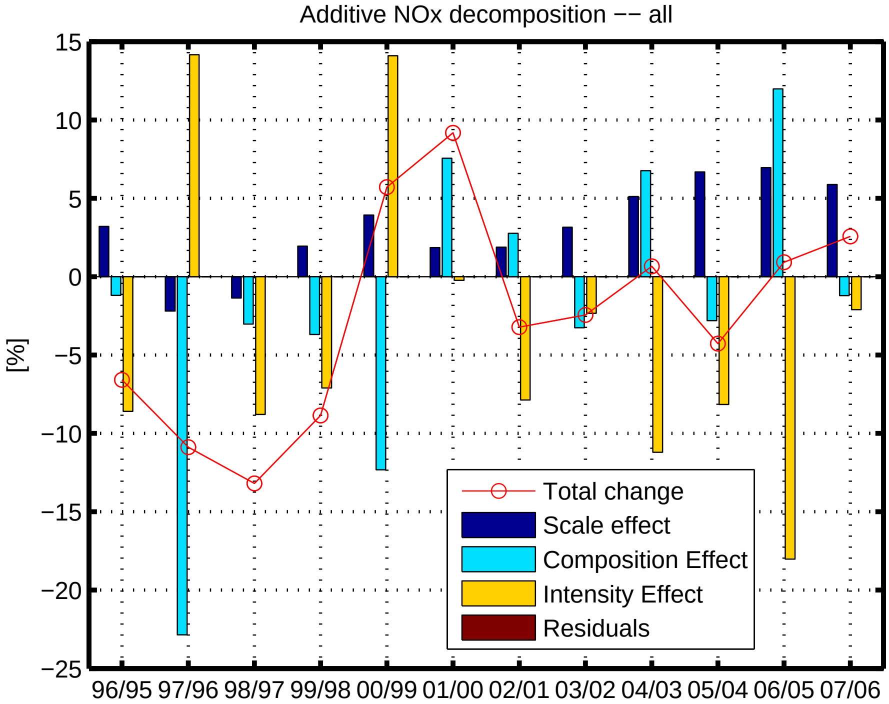

Figure 3.6: 3 factor decomposition (PM), 1995 - 2007

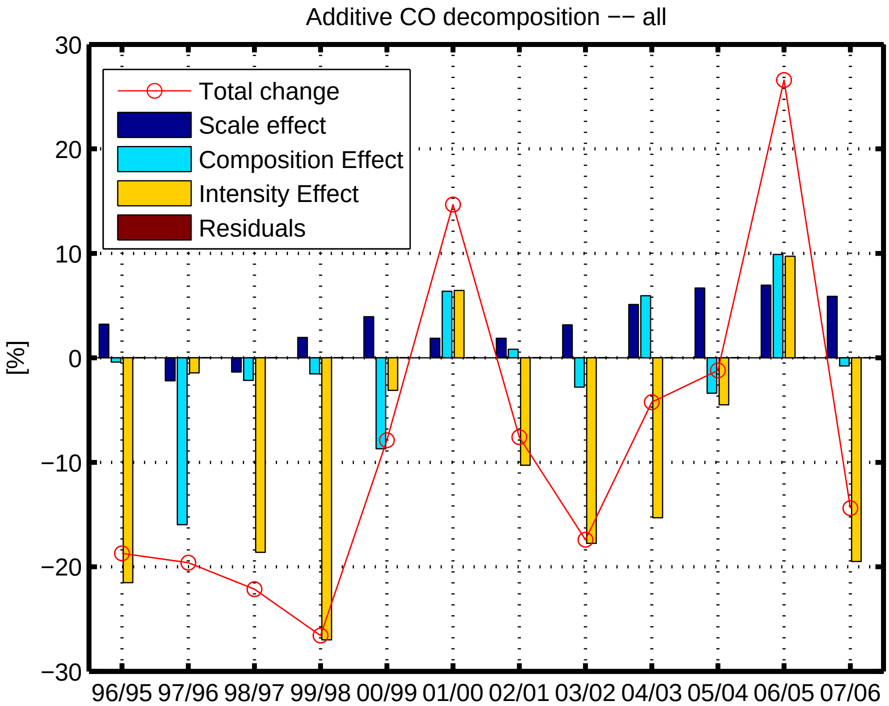

Figure 3.7: 3 factor decomposition (NOx), 1995 - 2007

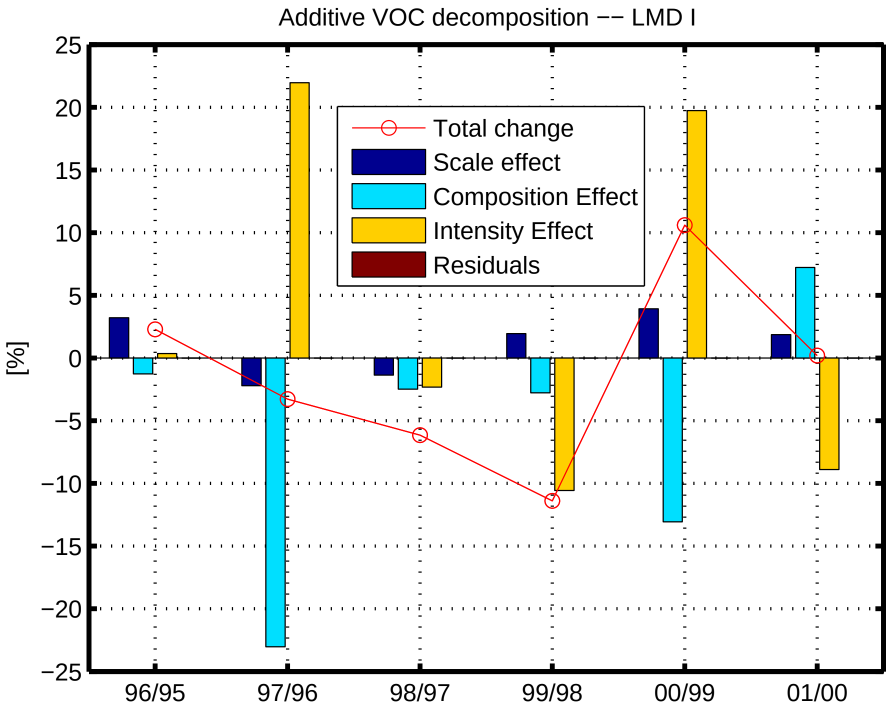

Figure 3.8: 3 factor decomposition (CO), 1995-2007

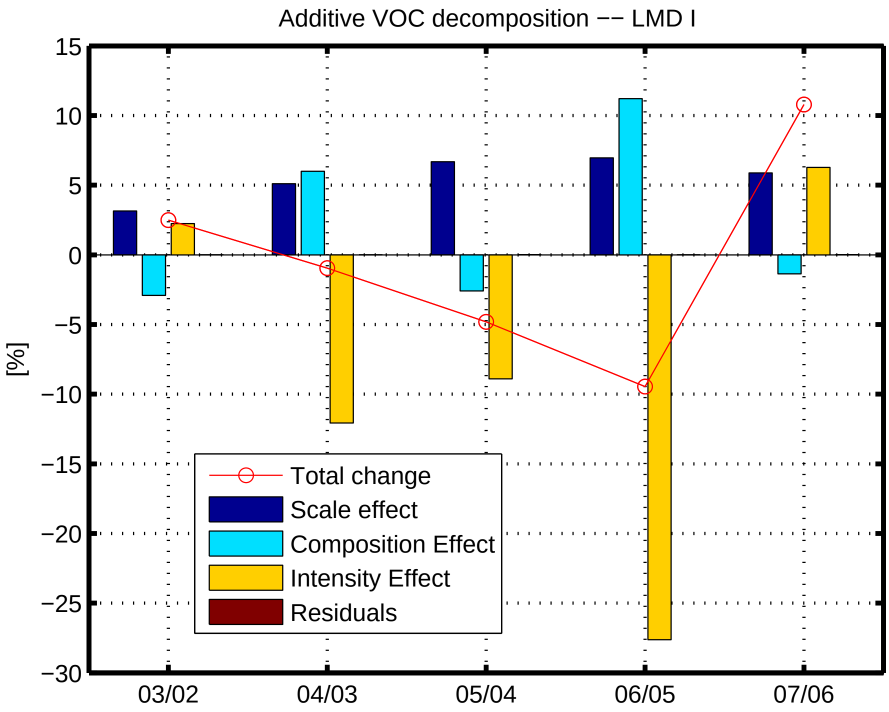

Figure 3.9: 3 factor decomposition (VOC),1995-2001

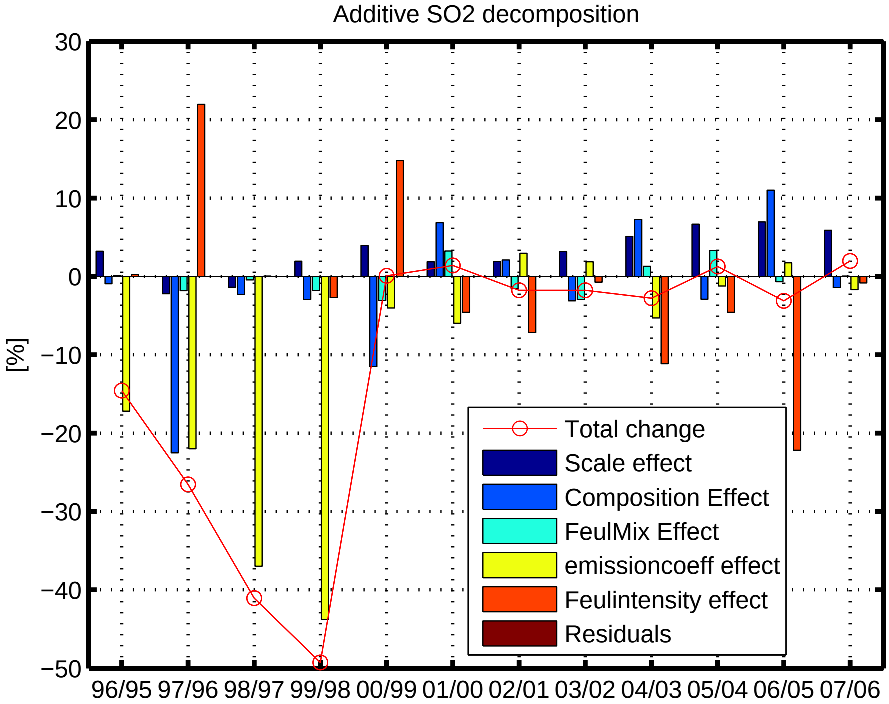

Figure 3.10: 3 factor decomposition (VOC), 2002-2007

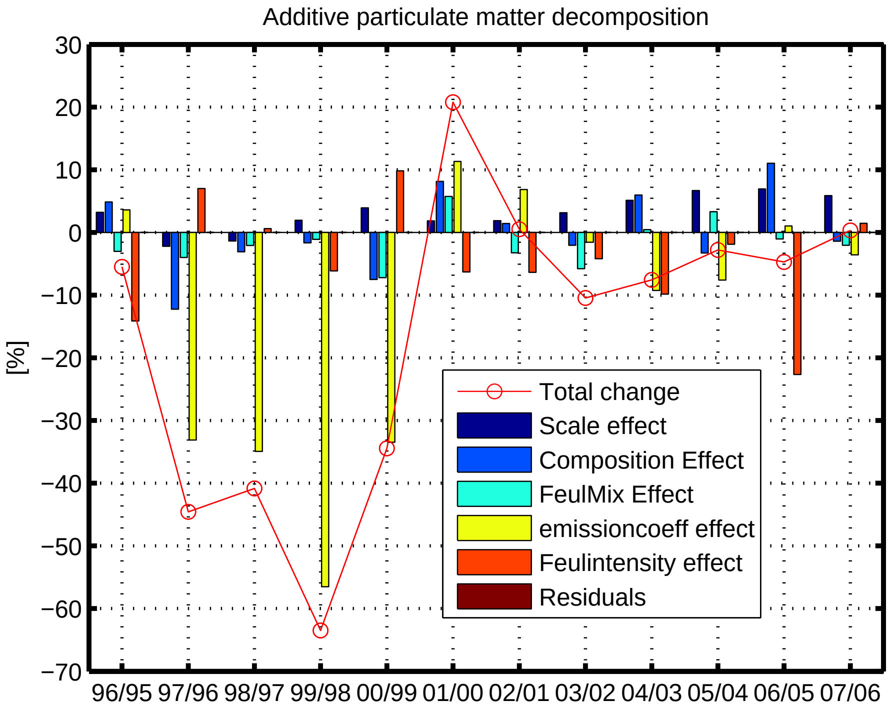

Figure 3.11: 5 factor decomposition (SO_2), 1995 - 2007

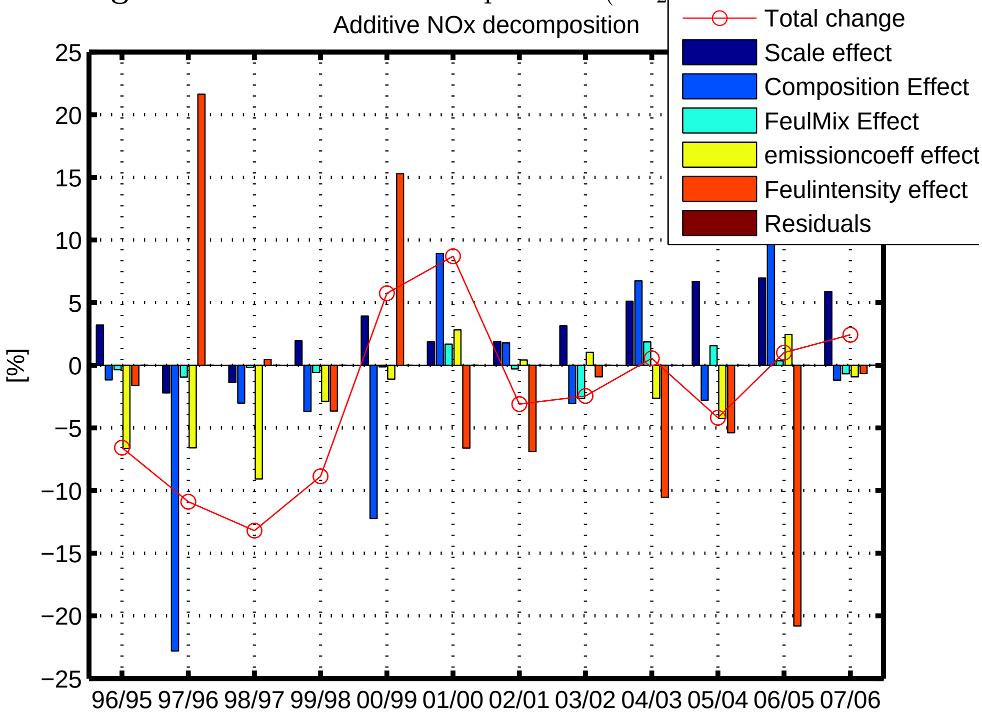

Figure 3.12: 5 factor decomposition (PM), 1995 - 2007

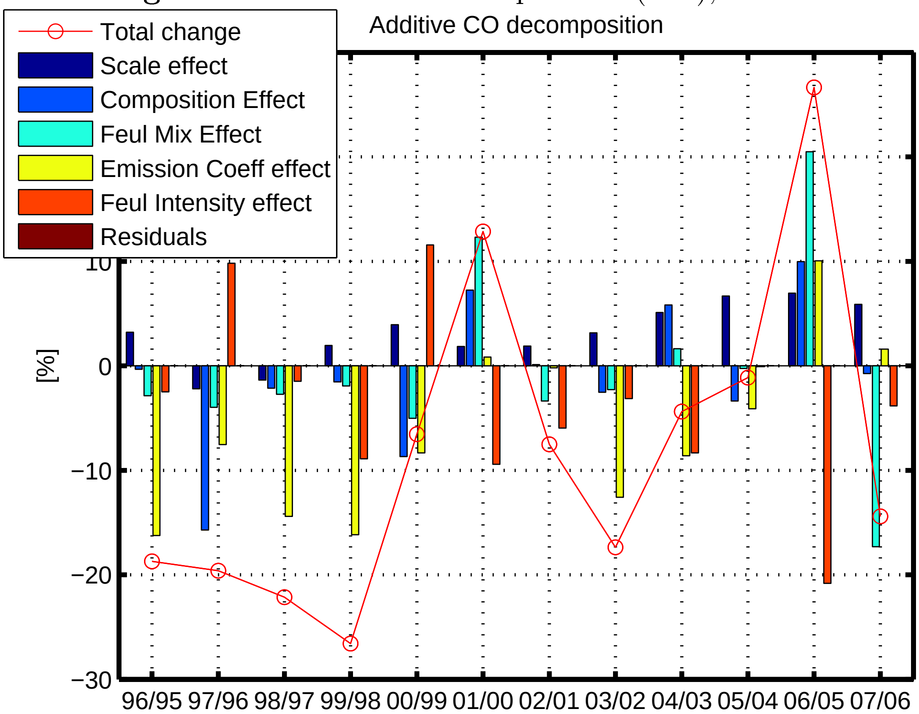

Figure 3.13: 5 factor decomposition (NOx), 1995 - 2007

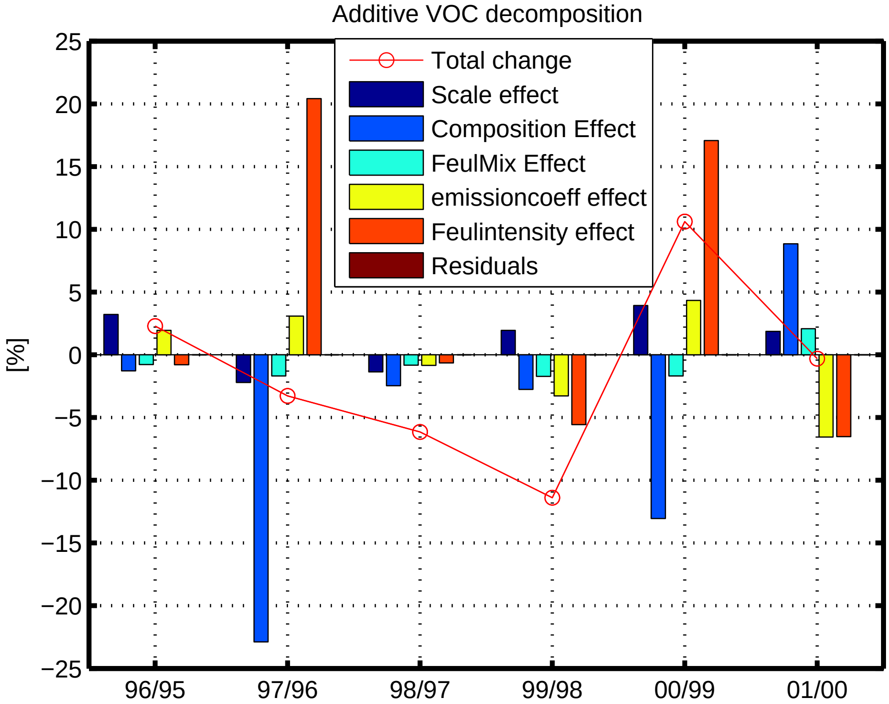

Figure 3.14: 5 factor decomposition (CO), 1995- 2007

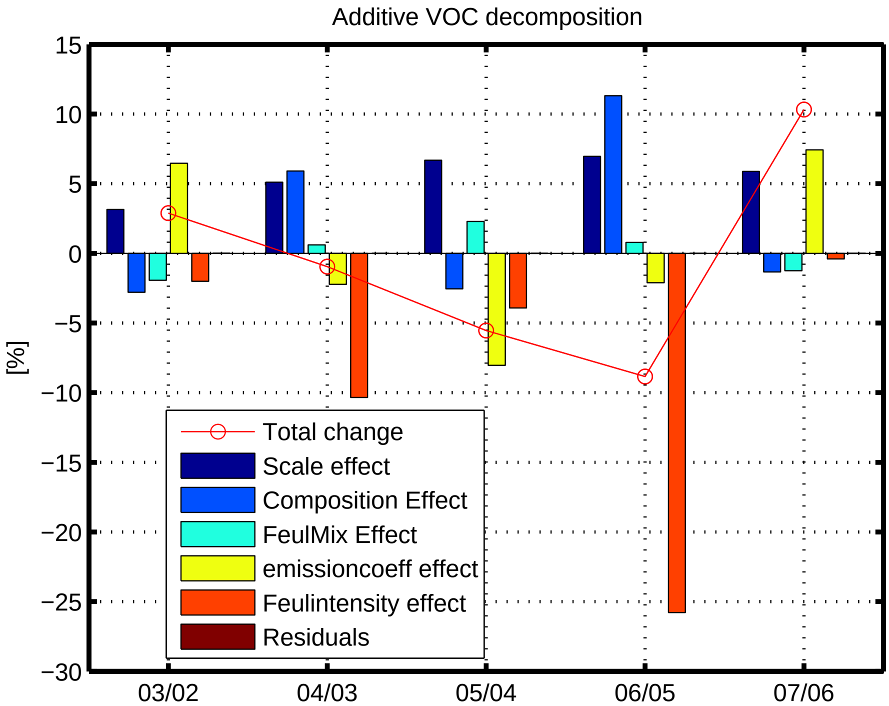

Table 3.1: Fuel Category

Broader categories of fuel	Refined category
Coal	Hard coal - energetic, low quality, sorted Lignite - energetic, low quality, sorted
Bio wood and other solid	Bio wood, Briquettes, Coke, Other solid fuel
Natural gas	Natural gas
Other gas	Blast furnace Gas, Coal gas, Coke gas, Generator gas, LPG, Other gas fuel
Liquid fuels	Gas oil, Gas oil - extra low sulphur, low sulphur, Naphta Heavy oil, Middle oil, Liquid fuel

Table 3.2: Comparison of Emission Coefficients

SOx	1995	2000	2005	Poland	Hungary	U.S.A
Coal (kg/toe)	55.71	11.78	10.50	27.7	81.2	41.4
Bio Wood and Other Solid	4.59	4.95	11.59	-	-	-
Natural Gas (kg/toe)	0	0	0	0	0	0
Other Gas	9.11	0.86	0.60	-	-	-
Oil (kg/toe)	35.08	16.84	12.32	13.4	15.2	3.5

NOx	1995	2000	2005	Poland	Hungary	U.S.A
Coal (kg/toe)	8.79	6.83	6.68	14.4	14.8	41.5
Bio Wood and Other Solid	6.54	8.74	4.26	-	-	-
Natural Gas (kg/toe)	5.05	2.63	2.18	3.3	2.7	3.1
Other Gas	4.44	1.48	4.04	-	-	-
Oil (kg/toe)	7.76	4.71	4.97	16.1	11.9	9.2

The values for Poland, Hungary and U.S.A are in the year of 1994, and taken from Viquier (1999).

Table 3.3: Cumulative contribution of factors (1995-2007)

	PM	SO2	NOX	CO
1995-2007				
Total change	-93.1%	-82.1%	-28.7%	-69.2%
Scale effect	2.4%	1.0%	-3.4%	5.8%
Composition effect	-9.2%	-17.5%	-21.8%	-18.0%
Fuel Intensity	-9.7%	9.3%	12.5%	4.5%
Fuel Mix	-9.0%	-3.6%	-2.7%	-21.4%
Emission Coefficient	-67.6%	-71.3%	-13.2%	-40.1%