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Dedication

To my parents, Arun and Neera.

Table of Contents

Table of Contents—*Continued*

List of Figures

List of Tables

List of Tables—*Continued*

List of Tables—*Continued*

ABSTRACT

The first essay of this dissertation focuses on studying the relationship between private politics and corporate environmentalism. This work analyzes the determinants and effects of two private political actions, boycotts and proxy contests. The analysis shows that: (i) the size of a firm is an important predictor of whether a firm will be chosen as a target of an activist campaign; (ii) firms headquartered in states with larger environmental constituencies are more likely to be targeted by activist campaigns; (iii) "dirty firms" (with larger relative or absolute emissions and/or high level of regulatory scrutiny) are more likely to become targets of an activist campaign; and (iv) private political campaigns are effective in improving the environmental performance of their targets.

The second essay examines the trends in Total Factor Productivity (TFP) and investigates the effects of major changes in the economy on measures of TFP in eight industries during the Interwar period from 1919 through 1939. TFP estimates show that each industry followed a different path of TFP change. There is no consistent evidence on large TFP decline during the years 1929-33 in the industries studied, as proposed in the literature. TFP measures also do not support the hypothesis that the 1930s were a period of interrupted TFP growth but there is evidence that five industries out of eight had higher productivity in the 1930s than in the 1920s. Regression analysis of major determinants of the TFP change for the motor vehicles and the cotton goods industry shows that TFP fell with increases in employment and strike activity. The NRA code might have also contributed to a decline in TFP.

Chapter 1
Introduction

This dissertation is characterized by the application of a wide array of micro econometric techniques and modeling frameworks for analyzing relationships in the fields of environmental economics and economic history. The first essay focuses on studying the relationship between private politics and corporate environmentalism. The second essay analyzes Total Factor Productivity (TFP) for eight industries over the time period 1919-1939 to investigate the effects of the National Recovery Administration (NRA) and other major institutional and technological changes in the economy on TFP.

The chapter titled "Determinants and Environmental Impact of Private Politics: An Empirical Analysis" focuses on the economics of activist campaigns. In the past decade there has been a surge in activist campaigns to force firms to behave in environmentally responsible ways. Despite the pervasiveness of activist campaigns like boycotts and a growing theoretical interest in the economics of activist campaigns, thus far, there is scarce empirical literature that studies these activist campaigns. In particular, there is no empirical evidence on the environmental impact of these activist campaigns. This shortcoming in the literature is addressed in this paper by analyzing the links between private politics and environmental performance of firms. Following the terminology coined by Baron (2001), "private politics" refers to the individual or collective actions initiated by public interest and activist groups to further their objectives without relying on the law or regulation. This chapter analyzes the determinants and effects of two such private political actions, boycotts and proxy contests. Environmental performance is measured by levels of toxic chemical releases and the adoption of two comprehensive environment management systems, total quality environmental management (TQEM) and ISO 14001, an international program to reduce industrial impacts on the environment.

Unique data on boycotts for the time period 1988-95 and for proxy votes for the time period 1988-2003 is utilized for this study. Main results are: (i) the size of a firm is an important predictor of whether a firm will be chosen as a target of an activist campaign; (ii) firms headquartered in states with larger environmental constituencies are more likely to be targeted by activist campaigns, providing some support for Baron's (2007) theory that activist campaigns will focus on "soft targets" (progressive firms); (iii) "dirty firms" (with larger relative or absolute emissions and/or high level of regulatory scrutiny) are more likely to become targets of an activist campaign; and (iv) private political campaigns are effective in improving the environmental performance of their targets. Boycotts are estimated to increase the probability of TQEM adoption by 27-32 percent, and proxy votes are estimated to increase this probability by 14-29 percent. A proxy vote against a firm increases the probability of ISO 14001 adoption by about 90 percent and spurs a statistically significant decline in toxic releases. This effect is even stronger if we limit our sample to early adopters of ISO 14001. Early adopters are four times more likely to certify to ISO 14001 if they had a proxy vote against them. All the estimates highlight the important role played by activist campaigns in spurring firms to self regulate their behavior.

The chapter titled "The Great Depression, the National Recovery Administration, Technological Innovation and Total Factor Productivity: 1919-1939" examines the trends in Total Factor Productivity (TFP) and investigates the effects of major changes in the economy on measures of TFP in a variety of industries between 1919 and 1939. Analysis is performed in two stages: First, total factor productivity (TFP) is estimated using panel data at the state level over the period 1919-1939 for eight key industries using a cost function approach. The TFP estimates help resolve a conflicting picture of TFP during the 1930s offered by Ohanian (2001) and Field (2003), based on Kendrick's (1961) data. Ohanian (2001) emphasizes the low TFP during the Depression years. On the other hand, Field (2003) stresses the "technological progressivity" of the Depression-era. In the second stage, I use a regression framework to identify the factors that can explain the changes in TFP over time.

TFP estimates show that each industry followed a different path of TFP change. The motor vehicles industry experienced declining TFP throughout the time period 1919-39, and had not yet returned to its peak level by 1939. Meanwhile, boots and shoes, bread manufacturing, cotton goods, and printing and publishing experienced an increase in TFP over the entire time period. The iron and steel industry TFP fluctuated greatly throughout the 1920s and 1930s. TFP in 1923 sunk 96 percent below its 1919 level, started recovering from 1925 and showed recovery till 1929. Iron and steel manufacturing TFP peaked again in 1933 before falling dramatically from 1933 through 1939. In contrast, to the economy wide descriptions by Cole & Ohanian (1999), there is no consistent evidence of a large TFP decline during the years 1929-33 in the industries studied. TFP estimates do not support the hypothesis that the 1930s were a period of interrupted TFP growth but there is some evidence that five industries out of eight had higher productivity in the 1930s than in the 1920s. Overall, this analysis provides some evidence in favor of Field (2003) and Field (2005) rather than Ohanian (2001) and Cole & Ohanian (1999). Second stage analysis for the motor vehicles and the cotton goods industry shows that TFP fell with increases in employment and strike activity. However, capacity utilization was positively related with TFP for the motor vehicles industry but had a negative relationship with TFP for cotton goods industry. The NRA code might have contributed to a decline in TFP as it led to incentives to raise employment, call strikes, and reduce capacity utilization. However, year fixed effects for 1933 and 1935 suggest that additional effects of the NRA were positive for both the industries.

The fourth chapter summarizes the results from previous chapters and discusses avenues for future research.

Chapter 2

Determinants and Environmental Impact of Private Politics: An Empirical Analysis

2.1 Introduction

In the past few years, environment policies of firms have come under close scrutiny. According to Smith (1970) consumers are becoming increasingly willing to withhold patronage to protest against perceived market abuses. In this changing milieu, activist campaigns are a powerful tool for raising awareness regarding the impact of corporate practices on workers, communities, and the environment. These campaigns have been greatly facilitated in recent years by the internet, which provides a cheap, easy and effective way of disseminating the information regarding these campaigns to millions of consumers. In the past decade there has been a surge in activist campaigns to force firms to behave in environmentally responsible ways. Specifically, boycotts have become a pervasive and potent way for consumers to express their discontent. There are several examples of successful boycott campaigns. Greenpeace organized a campaign against Coca-Cola to eliminate Hydro Fluoro Carbons (HFCs) from soda vending machines. This campaign aided by the use of the internet and the media, resulted in Coca-Cola conceding to the demand of Greenpeace. Short and virulent boycott efforts by the People of Ethical Treatment of Animals (PETA) led to animal rights reforms by McDonalds and other food retailers (Zwerdling 2002). Concessions were made by large lumber retailers to end marketing of old growth timber and adopt Forest Stewardship Council (FSC) standards due to boycotts by the Rainforest Action Network (RAN) (Barker 2002).

Following Baron (2001), "private politics" refers to campaigns by public interest groups targeted at audiences other than the government, including consumers and shareholders. Boycotts are one of the most prevalent forms of private politics. Although historically most boycotts fail to achieve their advertised objective, many firms take proactive measures to avoid becoming a target of such campaigns. Quite often these measures result in significant policy changes and the adoption of environmentally responsible practices (Innes 2006). Thus, the influence of private politics reaches beyond the perceived "success" and "failure" of campaigns.

Despite the theoretical and practical interest in activist campaigns, the empirical literature on this field is very limited. We address this shortcoming by focusing on two types of campaigns initiated by private agents to promote corporate environmentalism: boycotts and proxy challenges.[1] This study has two main objectives. The **first** objective is to investigate the target selection process for these campaigns by studying the factors that determine whether or not a firm is targeted by activists for a campaign. The **second** objective is to analyze the impact of these campaigns on the environmental performance of firms.

Prior studies the effects of boycotts on the share price of target firms, generally identify a negative effect.[2] Still the perception remains that these campaigns have insignificant short-term effects and no long-term effects. In this paper, we identify another channel, namely, the environmental performance of firms, through which these campaigns can have an effect. We investigate if activist campaigns spur target

[1] Proxy challenges or proxy votes refer to shareholder resolutions. These are proposals submitted by stockholders/shareholders in a publicly traded company to the company management to be voted on in the next annual proxy vote. Shareholders affect change in managements policies and procedures through participation in the company's annual general meeting either in person, or more commonly, by proxy voting remotely, via mail, phone, or online. Proxy voting is the primary means by which shareholders are able to direct company management to act in a socially responsible manner.(Source: http://www.socialinvest.org/projects/advocacy/)

[2] Pruitt & Freidman (1986); Pruitt, White & White (1988) and Davidson, Worrell & El-Jelly (1995).

firms to improve their environmental performance, measured by the adoption of comprehensive environment management systems (EMS), ISO 14001 certification, and reduction of toxic chemical releases.[3] EMS and ISO 14001 are voluntary environmental initiatives. Broadly, EMS can be defined as a set of rules, policies, strategies and administrative procedures that are developed by an organization internally to meet their environmental goals (Coglianese & Nash 2002). Participants of EMS commit themselves to reducing the negative impact of their activities on the environment (Delmas 2000). ISO 14001 is set of mandatory environmental guidelines that can be audited by an accredited third party for certification or registration.[4] The environmental and economic benefits associated with ISO 14001 can also be attained by an in-house EMS. However, ISO 14001 has the additional benefit of signaling a firm's commitment to environmental management to external stakeholders (Jiang & Bansal 2003). The basic premise of this paper is that businesses will undertake proactive environmental initiatives to avoid becoming the target of activist campaigns. We have focused on EMS and ISO 14001 as the outcome variables as several studies have documented the effectiveness of these voluntary programs in reduction of toxic releases(Anton, Deltas & Khanna (2004); Innes, Khanna & Sam (2008); Potoski & Prakash (2005) and Szymanski & Tiwari (2004)).

We utilize a unique dataset on boycotts and proxy votes for our empirical analysis. The data on boycotts provide information on environmental boycotts over the period 1988-1995. The dataset on proxy votes is longer, spaning the time period 1988-2003. To identify the variables that play an important part in target selection, we estimate a cross-sectional probit model for boycotts and a random-effects (panel) probit model for proxy votes. We find that the size of a firm is an important predictor of whether

[3]Adoption of EMS, ISO 14001, and reduction of toxic chemical releases are expected to have long term effects on the environmental performance of the firms. However, we have not quantified the long term effects in this paper.

[4]See section IV of this paper for more details on ISO 14001 certification.

a firm will be chosen as a target of an activist campaign. Baron (2006) theory predicts activist campaigns will focus on "soft targets" (progressive firms); we find mixed evidence for this prediction. On one hand, firms that operate in states with larger environmental constituencies are more susceptible to environmental pressure and are more likely to be targeted for boycott campaigns. On the other hand, we also find that the firms that are relatively high emitters of toxic substances (relative to industry norms) are also more likely to be targeted for a boycott. In case of proxy votes we find that their primary focus is on "dirty firms", that is firms that are high emitters and are subject to more regulatory scrutiny by the government, as measured by the number of inspections. However, firms operating in states with large environmental constituencies are not the target of proxy votes.

We evaluated the environmental impact of activist campaigns by specifying: (i) a comprehensive Environmental Management System (EMS) adoption equation; (ii) an ISO 14001 equation; and (iii) a pollution equation. We find that boycott and proxy vote variable exerted statistically significant effect on EMS adoption. Boycotts increase the probability of adoption of an environmental management system by 27-32 percent and proxy votes increase this probability by 14-29 percent. Tests for endogeneity of the boycott and proxy vote variables in the EMS adoption equation revealed absence of endogeneity.

The ISO 14001 equation and the pollution equation take into account the effect of only one political action - proxy votes. The timing of boycotts does not allow for testing the effect of the boycott variable on ISO 1400 certification and emissions of a firm. We find that the proxy vote against a firm increases the probability of ISO 14001 certification by about 90 percent. This effect is even stronger if we limit the sample to early adopters of ISO 14001. Early adopters are four times more likely to certify to ISO 14001 if they had a proxy vote against them. After accounting for sample selection bias and controlling for other firm-specific characteristics in the pollution equation, we find that proxy votes lead to a statistically significant decline in toxic releases. We estimate ISO 14001 certification equation as piece-wise exponential hazard model and Cox proportional hazard model.[5] The pollution equation is estimated as both random effects and fixed effects models.

This paper contributes to the existing literature by identifying the firm characteristics that increase the odds of a firm being targeted for activist campaigns and by analyzing the link between private politics and environmental performance of firms. We recognize new avenues through which private politics affects firm behavior. To the best of our knowledge, this work is the first in literature to empirically study how targeted firms are selected, first to perform an in-depth analysis of proxy votes as a campaign tactic and also the first to evaluate environmental impacts of these campaigns.

The rest of the paper is organized as follows. Section 2 presents the literature review. Section 3 discusses the conceptual framework, the empirical model and the data used in the study. Section 4 describes the estimation results. Concluding remarks follow in section 5.

2.2 Literature Review

Private politics is an emerging area of research. Although significant advances in the theory of private politics have been achieved (Baron (2001, 2002, 2003); Innes (2006)), empirical research is still very limited. This subsection reviews the theoretical and

[5]Proxy vote variable in ISO 14001 equation could be potentially endogenous as it could be in case of EMS adoption equation. We are exploring the literature to find a methodology to test for potential endogeneity of proxy vote variable in ISO 14001 equation. The results reported in this paper do not test or correct for potential endogeneity of proxy vote variable.

empirical research on private politics. We have focused on boycotts for reviewing empirical literature as there is no study that conducts an in-depth analysis of proxy votes as a campaign tactic.

The theory of private politics presented by Baron (2002) studies the organization of private politics and policies resulting from it. His theory is based mainly on two models. One model focuses on the public's response in the form of a boycott to information about the policies of the firm. The second model focuses on the bargaining between the activist and the firm in order to resolve the issue and then end the boycott. Based on theoretical models, he draws conclusions regarding effectiveness of activists in achieving their goals, susceptibility of firms as targets of activists and issues that are more likely to attract boycotts. He concludes that firms that have valuable brands, a weaker prior reputation for intransigence, practices resulting in greater perceived harm, association with potentially more serious issues, and operation in more communitarian societies and products with close substitutes make them better targets for boycotts. Issues that are more likely to attract boycotts are serious, involve a product with lower switching costs and raise moral concerns. Further, these issues are related to more communitarian societies and citizens can make a greater impact by adopting them.

The assumption of asymmetric information drives most of results of Baron (2002) and Baron (2003). Baron (2001) and Baron (2003) show that the boycotts are unlikely to arise in equilibrium under the assumption of symmetric information. Boycotts are avoided as targeted firms agree to the demands of the activists. Alternatively, Baron (2002) and Baron (2003) assume asymmetric information and show that boycotts can only arise due to asymmetric information regarding the intransigency of the firm and environmental organization (EO). In this model, boycotts can persist indefinitely if both the parties are intransigent.

Innes (2006) notes boycotts do arise in cases where information is quite good (or symmetric). He cites Friedman (1999), who in his survey of boycott leaders finds that boycotters take into account the known susceptibility of both a potential boycott target (measured by reputation, financial position, visibility in the public (consumer) eye and propensity of responsiveness) and the target consumer audience, while designing their campaigns. In view of these cases, Innes (2006) addresses the issue why boycotts might arise under the assumptions of symmetric information and imperfect competition. Innes (2006) models strategic interactions between non-identical duopolistic firms and EO that advocates an "environmentally friendly" production practice. The EO can invest in a boycott of a "brown" firm if it does not adopt "green" environmental practices. He finds that two types of boycotts are possible in equilibrium: (a) a small persistent boycott that targets the small firm in the industry and (b) a large transitory boycott against a big firm in the industry that prompts the big firm to quickly accede to the boycott's demands.

Despite the theoretical interest and an increase in the number of boycotts and responses to boycotts, there has been little progress in empirical work that studies the different channels through which boycotts can make an impact. Most of the previous literature has only tested the hypothesis that the boycotts affect a firm by reducing the share price and firm value. However, the empirical evidence based on event studies of the boycotts is inconclusive. Pruitt & Freidman (1986) assess the impact of 21 consumer boycott announcements on the wealth of stockholders of target firms by employing event-time methodology. They find that consumer boycott announcements have a highly significant negative effect on the stock prices of the target firms. The overall market value of the target firms dropped by almost $120 million over the two month post announcement period. In another study Pruitt et al. (1988) analyze the impact of union-sponsored boycotts on the stock prices of the targeted firms. They also find that union boycott announcements lead to short term decline in the stock prices of the target firms.

Davidson et al. (1995) examine a larger sample of boycotts over a longer period of time. They analyze a 23-year period (1969-91) to study the investors' reactions to announcements of product boycotts and stock divestitures. In a divestiture a group announces that it is selling the company's common stock and refuses to keep company securities in the portfolio. Both the boycott and divestiture are means of pressuring firms. They find that the announcements of boycotts have significant negative market reactions but stock divestitures announcements did not result in any kind of market reactions. However, Sergius, Akhigbe & Springer (1997) find contrary evidence. They focus on publicly traded firms that were target of a boycott or threat of a boycott over the time period 1980-1993 and use event study methodology. They find that the value of target firms increases, on average, by 0.76 percent on the day the news of the boycott becomes public. According to Sergius et al. (1997) these findings can be justified by the fact that the boycott targets do not passively accept being boycotted but rather take measures to counteract the effect of boycotts. These results indicate that these measures were working. Teoh, Welch & Wazzan (1999) analyze the impact of South African boycotts. They find that there was no significant effect of this boycott on US firms or on shares traded in Johannesburg Stock Exchange.

Part of the empirical work in this area of research focuses on the strategies used by the activists to influence firms. Epstein & Schnietz (2002) analyze the effect on the stock prices of firms identified as "abusive" by the anti-globalization demonstrations at the 1999 Seattle WTO meeting. They find that the firms identified as abusive due to environmental damaging activities had significantly lower stock returns, whereas firms with abusive labor practices experienced normal returns. This finding suggests that the issue itself is important for the success of the campaign. Issues that resonate with public are more likely to be successful.

One motivation of our study is to analyze the role played by activist campaigns in adoption of EMS, ISO 14001 registration and reduction of toxic releases of a firm. Several studies have examined firms' motives for adopting EMSs and certifying to ISO 14001 (Dasgupta, Hettige & Wheeler (2000); Khanna & Anton (2002), Anton et al. (2004); Delmas (2000); Nakamura, Takahashi & Vertinsky (2001); Bansal & Hunter (2003); King, Lenox & Terlaak (2005); Potoski & Prakash (2005); Gonzalez-Benito & Gonzalez-Benito (2005); G., Mzoughi & Thomas (2008); Delmas & Montiel (2008); and Gonzalez-Benito & Gonzalez-Benito (2008)). These studies identify environmental liability threats, high cost of compliance, high level of emissions, regulatory pressures and pressures from consumers, investors, and public as main factors driving adoption of EMSs. The motivations for adopting ISO 14001 are very similar to the motivations for adopting EMS. Research on ISO 14001 certification suggests firm size, previous 9000 certification, consumer demands, proactive operations functions, reinforcement of commitment to environment and attempt to curb regulatory and consumer pressures act as main determinants of ISO 14001 certifications. Several of these studies have also analyzed the impact of these programs on toxic releases. Anton et al. (2004) find that a more comprehensive EMS lead to lower toxic emissions per unit particularly for firms with higher pollution intensity in the past. Innes et al. (2008) report that Total Quality Environment Management had a significant negative impact on 33/50 releases. Potoski & Prakash (2005) find that ISO 14001 certified facilities reduce their emissions more than non-certified facilities. Szymanski & Tiwari (2004) determine the length of time after which a given company has implemented ISO 14001 experiences emissions reductions. Their results show that 75 percent of the companies experienced a reduction in their emissions, among which 53 percent reduced their emissions after the first year of adoption.

Most of the literature on ISO 14001 certification and EMS adoption discusses the importance of unofficial pressure from consumers, local communities, investors and public in adoption of these programs. However, the only way these studies measure this pressure is by measuring proximity to consumers and/or membership in environmental groups like Sierra club and National Wildlife Federation. Other than Sam & Innes (2008) none of these studies take into account the actions of these environmental groups or other stake holders. In this study we clearly identify pressure imposed by public and stakeholders by analyzing boycotts and proxy votes. Sam & Innes (2008) take into account threat of boycotts in their study. Their measure of boycott is if a firm operates in an SIC that was subject to a boycott. Though none of the firms in their sample were actually boycotted but they still find that the threat of boycott is a significant factor in explaining corporate environmentalism. However, they do not study the relationship between the activist campaigns and environmental behavior. We are not aware of any other study that ties environmental behavior of a firm to the effect of activist campaigns.

2.3 Methodology

In this section we lay out the hypotheses that we seek to test in this paper. These hypotheses will aid us in identifying the main determinants of target selection and in explaining the effects of activist campaigns. We focus on the yet unexplored linkages between environmental performance of a firm and activist campaigns. Our first hypothesis identifies the factors that make a firm a good target for an activist campaign.

2.3.1 Boycott and Proxy Vote Equations

Empirical Framework

Hypothesis I: A firm is more likely to be targeted by a boycott[6] if it:
(a) is large and visible,
(b) has more contact with final consumers,
(c) is located in an environmentalist state,
(d) has practices that result in greater harm.

It is reasonable to assume that the objective of an activist campaign is not only to pressure the firm into compliance but also to create awareness about the issue. These objectives are easily satisfied if a firm is big and is in public eye. Widespread and prominent news media coverage makes it more likely that the targeted firm will concede to the demands of the boycotters (Friedman 1999). It is not possible to determine the extent of media coverage for each boycott but it can be assumed that if a firm is large and visible, any campaign against it will generate a lot of media attention. This will result in negative publicity for the firm and more awareness for the issue at stake. The size and visibility of the firm is measured by the variable - number of employees (NOEMPLOYEES) employed by the firm. We have also used annual sales of a firm (SALES) as a measure of its size.

If the firm sells products directly to the final consumers, a boycott is expected to be more effective. According to Baron (2002) firms that produce consumer products make better targets than the firms that produce industrial products. Profits are expected to be more responsive to boycotts of consumer product companies due to proximity to consumers. The objective of a boycott is to usually include consumers in the boycott and affect sales of the product. However, this is not possible if the product is an intermediate good and not visible to the consumers. Contact with final consumers is identified by creating a binary variable FINALGOOD that takes a value one if a firm sells a product directly to the consumers.

[6]We have reported the boycotted firms and the type of boycott in Appendix A in Table A-1

The boycotts should be more effective against firms that are located in pro-environment states. We identify a state as being pro environment by using environment related and state specific variables. Sierra club membership (SIERRA)[7], if state has strict environment liability statute (STRICT), spending on air quality programs (SPENDAIRQUA) and expenditure on natural resources (NREXPT) determine if a state is pro-environment. State specific variables include percentage of college degrees (EDUC), number of lawyers per capita (LAWYERSPERCAP), if state has a right to work statute (RIGHTTOWORK) and average income (AVERAGEINCOME). These variables act as proxies for progressiveness of the state. Each of these variables is specified for the state in which the firm has its headquarters.[8]

Firms with practices that result in greater perceived harm make a better target as it is easier to get public support against them. One way to measure harm is in terms of impact of a firm's practices on environment. A firm's environmental performance can be measured by toxic releases of the firm and the number of superfund sites for which firm is a potentially responsible party (PRP).[9] We create the CAAEMISSIONS variable that measures total air emissions at the firm level. We have created another variable RELEMISSIONS that measures the emissions of the firm relative to the industry level emissions. This variable is included to take into account if the activist campaigns focus on firms with absolute high level of emissions or high level of emissions with respect to the industry. However, it is not clear if an activist campaign will focus on self interested firms or morally managed firms (here by, measured by environmental performance). According to Baron (2006), the activist campaign

[7]Sierra club was founded on May 28, 1892 in San Francisco, California. It is America's oldest and largest grassroots environmental organization. Sierra club membership indicates the number of people that registered as a member in a particular state in a given year.

[8]We are in the process of constructing facility weighted measures of state specific variables.

[9]We recently acquired data on this variable. Hence, this variable is not included in the current analysis.

will focus on a morally managed firm as they are softer targets. The inclusion of these variables helps us identify if the activist campaigns target the firms that are under-performers (at least) in terms of environmental performance or the firms that are morally managed.[10]

Same set of factors also determine if the firm is targeted for a proxy vote. All the proxy votes are cast on environment related issues so the linkage to environment specific variables is stronger. Table A-2 in appendix reports the main issues taken on through the proxy votes. We control for industry specific effects by including the binary variables for the SIC codes of industries most heavily represented in our sample. The industries represented by each SIC code are reported in Table A-3. We have also included inspections variable in the proxy vote equation. We believe that stakeholders are more likely to have access to hard to come by firm-specific information as compared to activists. We estimate boycott and proxy vote equations separately.

Econometric Model

We estimate the boycott equation using a Probit specification:

$$B_i^* = X_i \alpha + u_i \tag{2.1}$$

where, B_i^* measures net gain if a firm is chosen as a boycott target. X_i is a vector of explanatory variables that determine if a firm is chosen as a boycott target. The error component is assumed to be normally distributed with zero mean and variance one. The binary variable $BOYCOTT$ that indicates if a firm is boycotted or not is defined by:

[10] A firm is morally managed if its behavior is motivated by moral duty

$$BOYCOTT_i = 1 \ if \ B_i^* > 0 \tag{2.2}$$

$$BOYCOTT_i = 0 \ otherwise \tag{2.3}$$

The boycott variable, BOYCOTT takes a value 1 if the firm is boycotted over the time period 1988-95.[11] All the explanatory variables are lagged cross-section variables. We have lagged all the explanatory variables to year 1988 in order to take into account the timing of boycotts. The boycotts are spread over the entire time period 1988-95. Lagging the explanatory variables to 1988 ensures that we are capturing all the required information on firms that determines if it would be boycotted. The explanatory variables consist of SALES, NOEMPLOYEES, SIERRA, STRICT, SPENDAIRQUA, RIGHTTOWORK, EDUC, LAWYERSPERCAP, AVERAGEINCOME, RELEMISSIONS, CAAEMISSIONS[12] and dummy variables for major SIC codes to control for industry specific effects.

Due to the panel nature of the proxy vote variable, the proxy vote equation is estimated using a random effects probit specification.[13] We have chosen random effects model on theoretical grounds as our sample of S&P firms is a relatively small sample from the overall sample of the firms. Also, according to Greene (2000) the probit model does not lend itself well to fixed effects. The model is as follows:

$$P_{it}^* = X_{it}\beta + u_{it} \tag{2.4}$$

[11]This does not require the boycott to begin in 1988 and end in 1995. For example, a firm that faced a boycott lasting from 1991 to 1992 is also a part of the sample.

[12]We have used air releases data for 1989 instead of year 1988. This is done to minimize any data reporting problems. Toxic Release Inventory (TRI) was released by the EPA for the first time in 1988. This year being the first year of data reporting could be potentially problematic.

[13]Proxy vote equation allows to take into account the role of changes in explanatory variables overtime, whereas Boycott equation does not. The boycott equation is specified as a cross-section equation due to limited information on timing of boycotts.

where, P_{it}^{*} measures net gain from choosing a firm as a proxy vote target. X_{it} is a vector of explanatory variables that determine if a firm is chosen as a proxy vote target. The indicator variable $PROXYVOTE$ captures if a firm is a target of a proxy vote or not and is defined as:

$$PROXYVOTE_{it} = 1 \ \ if \ \ P_{it}^{*} > 0 \tag{2.5}$$

$$PROXYVOTE_{it} = 0 \ \ otherwise \tag{2.6}$$

The error term is decomposed in two components as in the linear case:

$$u_{it} = \alpha_i + \eta_{it} \tag{2.7}$$

We assume that η_{it} $i.i.d.N(0,1)$, and that the αs are independent random draws from a normal distribution. This implies that: $Var(u_{it}) = 1 + \sigma_{\alpha}^{2}$. The common error component α_i implies that within units u_{it} are correlated. This correlation is given by:

$$Corr(u_{it}, u_{is}, t \neq s) \equiv \rho = \frac{\sigma_{\alpha}^{2}}{1 + \sigma_{\alpha}^{2}} \tag{2.8}$$

Random-effects probit makes the key assumption that $Cov(X_{it}, \alpha_i) = 0$. This assumption is critical in order to get consistent estimates of β. If various realizations of P_{it} were independent for each i, we could employ the standard probit technique. However, estimation is much more difficult as Pit are correlated and hence result in a complicated t-fold integral. Butler & Moffitt (1982) show that it is possible to reduce the t-fold integral to a single integral whose integrand is a product of one normal density and T differences of normal cdf's. Even the evaluation of this integral is quite burdensome. Butler & Moffitt (1982) suggest an approach that allows evaluating this one-dimensional integral by an approximation known as Gauss-Hermite quadrature.[14] This method requires the assumption that correlation is the same across all the time periods. This model is more appropriate when N is relatively large and T is relatively small, which is our case. However, the results from Gauss-Hermite method can be very sensitive to the number of quadrature "support points" chosen. We have tested for the stability of results by retrying the model with different number of points and ensuring that the results do not vary too much by the number of points used. We have also tested for the presence of unobserved effect *rho*, that is, within units correlation.

The proxy vote variable, PROXYVOTE is defined for each year from 1988-2003. It takes a value 1 if there was a proxy vote against the firm in that particular year. We have limited our study period to 1989-2003. The year 1988 is excluded due to the poor quality of data on emissions. The data after year 2003 is excluded due to unavailability of data on several other variables. All the state specific variables are cross-section variables for year 1988. These variables are not expected to change overtime hence it is reasonable to use 1988 values. All other explanatory variables are current period variables. The explanatory variables are different from the boycott equation only in terms of timing.

2.3.2 EMS Adoption and ISO 14001 Equations

Empirical Framework

[14] Gauss-Hermite quadrature is a means of approximating a non-closed form integral. The formula used for evaluating the necessary integral is Hermite integration formula $\int_{-\infty}^{+\infty} exp(-Z^2)g(Z)dZ = \sum_{j=1}^{G} w_j g(Z_j)$, where G is the number of evaluation points, w_j is the weight given to the jth evaluation point and $g(Z_j)$ is $g(Z)$ evaluated at the jth point of Z.

Hypothesis II: *A boycotted firm is more likely to adopt Environment Management System (EMS).*

Hypothesis III: *Proxy vote against a firm spurs it to adopt Environment Management System (EMS).*

Hypothesis IV: *Proxy vote against a firm makes it more likely that the firm will certify to ISO 14001.*

Conceptually, a prior boycott may promote EMS adoption as a strategy to counter the negative publicity associated with the boycott and to avoid a future boycott, with a previously targeted firm likely to be more sensitive to the prospective threat of further campaigns. However, given the timing of boycotts and EMS, it is reasonable to assume that a firm's decision to not adopt EMS will not result in a boycott.[15] The boycott equation is the same as defined in *hypothesis 1*. We have not tested for the effect of boycotts on ISO 14001 certification. ISO 14001 certification program started in 1996; though our sample of boycotts covers the time period 1988-95, majority of boycotts occurred before 1991. Due to large time lag we do not expect the boycotts to have any effect on ISO 14001 certification.

We are going to discuss determinants of EMS adoption and ISO 14001 certification together as both these programs are motivated by the same set of characteristics. However, the econometric models for these two equations are very different and discussed separately. We have followed the previous literature on EMS adoption and ISO 14001 certification (specifically, Anton et al. (2004); Innes et al. (2008); King et al. (2005) and Potoski & Prakash (2005)) in order to identify the factors that influence a firm's decision to adopt EMS. We include two variables that measure a firm's size, namely, sales (SALES) and number of employees employed by the firm (NOEMPLOYEES). Larger firms are more likely to adopt EMS as they have po-

[15] This issue is discussed in more detail in *econometric model* section.

tentially lower costs and larger resources for environmental programs. We have also included total assets (TOTALASSETS) as a measure of firm's size. Firm might adopt EMS/ISO 14001 in order to attract "green" consumers. This effect is captured by including the final good dummy (FINALGOOD), that measures proximity to final consumers (Arora & Cason (1996) and Khanna & Damon (1999)). Firms might also adopt EMS/ ISO 14001 and reduce pollution voluntarily in order to preempt lobbying by environmental groups for tighter standards. The effect of proactive environmental efforts is likely to be greater in states with larger environmental constituencies (Potoski & Prakash 2005). This effect is captured by per-capita Sierra club membership (SIERRA). We have also included interaction between FINALGOOD and SIERRA to capture the fact that more visible firms are more likely to be targeted.

Firms with larger expenditure on R&D might be able to develop technologies to lower their abatement costs and hence be more willing to adopt voluntary systems to improve environmental performance. According to Anton et al. (2004) the firms with newer equipment might be able to reduce the emissions at lower cost and hence more inclined to join environmental programs like EMS. This effect is captured by the variable AGE, which is the ratio of net to gross assets.[16] None of the papers studying ISO 14001 include AGE and R&D variables in ISO 14001 certification equation, hence we have omitted these two variables from ISO 14001 equation. The variable EPAINSPECTIONS measures the number of inspections made against a firm. Larger number of inspections against a firm increase the possibility of higher penalties being levied against the firm. The firm might try to diffuse this situation by getting involved in voluntary environment programs. Potoski & Prakash (2005) assert that firms that receive more inspections may be more likely to join ISO 14001. By joining ISO 14001,

[16]We included AGE and R&D variables in earlier specifications. AGE variable led us to drop eight percent of the observations and R&D about half of the sample. Since none of these variables were significant in any of the specifications we excluded these variables from later estimations.

the firms seek to use perceived standing of ISO 14001 among regulators as a means to signal to the regulatory authorities and consumers that they are proactively working on improving their environmental performance and reducing the waste generation. Similar motivation works for EMS adoption. Similarly, the firms with higher CAAEMISSIONS or RELEMISSIONS can mitigate the pressure from consumers and stake holders by adopting EMS. Firms may also adopt EMS/ISO 14001 in order to increase the costs of their rivals. Firms operating in concentrated industries may be driven to adopt EMS/ISO 14001 in order to show exceptional environmental conduct and spur tighter standards and disadvantage rival firms. This effect is captured by including Herfindahl index (HERFINDEX) to measure the concentration of an industry. The inclusion of this variable also allows to test if market power is better for the environment than competition.

We include a variable called STRICT that takes into account if a firm's home state has strict liability statute. This variable is included to take into account the fact that firms with deeper pockets might adopt EMS in order to avoid potential liability for harm caused. These incentives are expected be larger in states with strict liability statute (Alberini & Austin 1999). EMS policies might provide clear roadmap to firm liability and hence deter firms from adoption EMS Innes et al. (2008). This effect is expected to be stronger for larger firms with more resources, hence we also include an interaction term between STRICT and NOEMPLOYEES. In case of ISO 14001, the substantial cost of ISO 14001 certification along with potential liability costs might also deter firms' from certifying to ISO 14001. We also control for socio-economic indicators for the state in which the firm operates. These variables are RIGHTTOWORK, LAWYERSPERCAP, SPENDAIRQUA, AVERAGEINCOME and EDUC. We have controlled for industry specific effects by including dummy variables for heavily represented industries.

Econometric Model

EMS Adoption Equation

Hypothesis II is tested by estimating equation given by:

$$R_i^* = \theta BOYCOTT_i + \beta W_i + u_{2i} \tag{2.9}$$

where, R_i^* measures net gain from responding to the survey sent by IRRC. W_i is a vector of explanatory variables that determine if a firm adopts EMS. Our data indicates that a firm responds to the survey only if it has adopted some kind of EMS.[17] Hence, we treat survey response as a signal that the firm has adopted EMS. The binary variable E that indicates if a firm adopts EMS or not is given by:

$$E_i = 1 \;\; if \;\; R_i^* > 0 \tag{2.10}$$

$$E_i = 0 \;\; otherwise \tag{2.11}$$

The error term is assumed to be normally distributed with mean 0 and variance σ_{u2}^2. W_i is a vector of independent variables that determine if a firm adopts EMS or not. Following Anton et al. (2004) all time-dependent variables are measured with a 5 year lag. This procedure is followed to take into account the fact that some firms might have adopted EMS before 1994-95 and also the adoption decision is more likely to depend on past firm attributes.

[17]The survey required the firms to respond if they adopted different kinds of environment management practices. Firm could choose from several different options. Each firm adopted at least one environment management practice.

We need to deal with two issues to estimate the EMS and boycott equation. First, in principle, the boycott variable could be endogenous in the EMS equation. For example, a socially responsible firm may be more likely to adopt EMS and either more or less likely to be a target of a boycott (ceteris paribus), implying correlation between errors in the two equations (equation 2.1 and equation 2.9). If the errors are correlated then we need to estimate the two equations by bivariate probit in order to get consistent and efficient parameter estimates. However, if the error terms are independent, then both the equations can be estimated independently by probit Maximum Likelihood (ML). We can test for correlation between the error terms by using Lagrange Multiplier (LM) test which determines if the error terms are correlated. We do not find the error terms to be correlated. Results are discussed in detail in the results section.

The second issue considered here is if a firm can become a target of a boycott due to not adopting an EMS system. As previously discussed this seems unlikely as the concept of Quality environment management was introduced for the first time in 1990. The majority of (about 75 percent) boycotts in our sample started before or in 1990. Hence it is reasonable to assume that it is unlikely that EMS adoption affected a firm's probability of being boycotted.[18]

We have specified a similar EMS adoption equation to test the hypothesis that the proxy vote can spur a firm into adopting EMS. The proxy vote variable is no longer a time-variant variable. We redefined the proxy vote variable (PROXYVC) as an indicator variable that takes a value one if there is a proxy vote against the firm in years 1988-91. This facilitates us in testing hypothesis III. We do not need to deal with the issue that the firms that do not adopt EMS are more likely to be a target of

[18]Practically, according to Maddala (1983) a system of two jointly endogenous binary choice variables is logically inconsistent.

a proxy vote. Since EMS came about only in 1991, it could not be a determinant in proxy votes occurring in and before 1991. The endogeneity issue is same as in case of boycott equation and EMS adoption equation. We specified a bivariate probit model to deal with this issue. We tested for correlation between the error terms. We find no evidence of the correlation and hence we can estimate the proxy vote equation and EMS adoption equations separately by probit.

ISO 14001 Certification Equation

We have employed duration analysis (hazard models) to test Hypothesis IV. Duration analysis has its origins in survival analysis. Survival analysis was originally developed as a statistical procedure in the field of epidemiology. It has been utilized extensively by researchers from economics, demographics, strategic management and organizational behavior. Survival analysis allows one to analyze a situation where an individual, family or firm, starts in an initial state and is either observed to exit the state or is censored. Recent treatments of duration analysis tend to focus on the hazard function. The hazard function allows us to approximate the probability of exiting the initial state within an interval, conditional on having survived up to the starting time of the interval. This set up is well suited to study ISO 14001 certification equation. Szymanski & Tiwari (2004) use the survival analysis to study the time interval from the moment a company adopts ISO 14001 until it reduces its toxic emissions. The hazard function allows us to approximate the probability of exit, in this case a firm certifying to ISO 14001 at a certain time period. This analysis also takes into account that the data is censored at the end of 2003. Our data is heavily right censored as only eight percent of the firms in our sample register by the end of 2003.

For our analysis, T is the time at which the firm exits the initial state, that is, it transitions to adopter from non-adopter. The cumulative distribution function of T is defined as:

$$F(t) = Pr(T \leq t), t \geq 0 \tag{2.12}$$

The survival function is specified as follows: $S(t) \equiv 1 - F(t) = Pr(T > t)$, and this gives the probability of surviving past time t. If we denote the probability density function of event occurrence as $f(t)$, the hazard function can be written as: $\frac{f(t)}{s(t)}$.

We have used the exponential model, piece-wise exponential model and Cox's proportional hazard model[19] for estimation of ISO 14001 certification equation. The first two models fall in the category of "parametric models" and third model is a "semi-parametric" model.[20] The main difference between parametric and semi-parametric models is that parametric models make assumption about the shape of the baseline hazard rate[21] and semi-parametric models like Cox's model do not require making any assumption about the shape of the baseline hazard rate. In case of the Cox model the hazard function is inferred from the data.[22] All these models fall in the category of "proportional hazard models". *Hazard proportionality* is the assumption that the proportion of two kinds of hazards is constant over time. The proportion

[19]See Cox (n.d.) for details. See Christensen & Greene (1976) and Wooldridge (2002) for introduction to survival analysis and hazard functions and Kalbfleisch & Prentice (2002) for details.

[20]The Cox model is also sometimes referred to an *non parametric* model. Cox's model has non-parametric aspect in the sense that it involves an unspecified function in the form of an arbitrary baseline hazard function. It is referred to as semi parametric here as it also incorporates a parametric modeling of the relationship between the hazard rate and specified covariates Kalbfleisch & Prentice (2002).

[21]Different models can be obtained by making different assumptions. Some examples are constant (exponential), Weibull and Gompertz. We can also estimate a piecewise exponential model as well.

[22]The fact that Cox models do not make any assumptions about the time-dependence of hazard rate, is big advantage of using Cox models. It implies potentially one less assumption will be violated as compared to parametric models. However, it should be kept in mind that Cox model is less efficient then a properly specified parametric model. The standard errors are bigger and more data might be needed to get statistically significant results.

is interpreted as a function of covariates. These covariates raise or lower the hazard rate in a proportional manner across time. We have tested for this assumption using Schoenfeld residuals after estimating Cox models.[23]

Conceptually, we can define the baseline hazard as $h_0(t)$. This baseline hazard is not influenced by any covariates. The hazard rate $h_i(t; x_i)$ is a function of a number of covariates. We assume that the proportion of $h_0(t)$ and $h_i(t; x_i)$ is constant under the assumption of hazard proportionality. x_i is the vector of explanatory variables (these explanatory variables can be time-varying) and proportional hazard is written as:

$$h_i(t; x_i) = h_0(t)\kappa(x_i) \tag{2.13}$$

Where $\kappa(x_i) > 0$ is a nonnegative function of x_i and $h_0(t) > 0$. The baseline hazard $h_0(t)$ is common to all the units in the population and individual hazard functions differ proportionally based on function $\kappa(x_i)$ of observed covariates. Usually $\kappa(x_i)$ is parameterized as $exp(x_i\beta)$, where β is vector of parameters. If we assume baseline risk to be constant, that is $h_0(t) = h_0$, we obtain the exponential regression model. Constant baseline hazard function implies that the process driving T is memory less. The probability of exit in the next period is independent of the time spent in the initial state.[24] This model seems to fit our data well as we do not expect that a firm is more or less likely to certify to ISO 14001 based on time elapsed since the beginning of the certification program. The Cox model is very similar to the exponential

[23] Test of assumption of proportional hazard is equivalent to testing for a non-zero slope in a generalized linear regression of the scaled Schoenfeld residuals on functions of time. A non-zero slope is an indication of a violation of the proportional hazard assumption. In addition to performing the test of non-zero slopes, we plotted rescaled residuals against time to confirm that the assumption of proportional hazard is not violated.

[24] Constant baseline assumption might seem a little odd as one might expect the hazard rate to go up and down over time. By assuming constant baseline hazard rate we are saying that the change is merely the result of independent variables, and hence the underlying (base) rate might, in fact, be constant.

model.[25] The only difference is that we do not estimate the baseline hazard function. We estimated both these models to test the robustness of our results. Our results are very similar in both these models (in terms of magnitude and significance) implying that the assumption of constant baseline hazard is appropriate for this model.

We also estimated piece-wise exponential and piece-wise Cox model[26] to take into account the fact that the majority of ISO 14001 certifications occur in year 2000 or after that. The piece-wise exponential model allows the hazard rate to be different (though constant) over pre-defined time intervals. The exponential model allows us to easily include separate time intervals in the full model (all the years). Our estimation results showed that hazard rate was significantly different over the different time periods (See coefficients on PERIOD in table 2.8). Further, we split our data in two parts: 1996-1999 and 2000-2003 and re-estimated models as exponential model and Cox model. Results are reported in tables 2.8 and 2.9 and discussed in results section. We considered the possibility that the proxy vote variable might be endogenous due the same reason it was endogenous in the EMS adoption equation. However, we are not aware of any procedure that allows us to test for potential endogeneity in the case of survival data.

2.3.3 Pollution Equation

Empirical Framework

[25]In the Cox model we additionally need to handle the issue of tied exits, that is, if firms exit at the same time. We have used Breslow approximation, Efron approximation and exact marginal approximation. Our results are generally robust to the use of any of these approximations.

[26]Piece-wise models cane be estimated in two different ways - 1) using the data for all the years and by introducing pre-determined intervals where the hazard rate might vary; or 2) estimating the model in two or more pieces. That is, the data is split in two or more shorter periods and models are re-estimated over shorter time periods.

Hypothesis V: *Proxy vote against a firm spurs it to reduce its toxic emissions.*

As in the case of ISO 14001 adoption equation, there is no counterpart of the pollution equation for boycotts. We do not have exact information on the start and end dates of boycotts, hence it is not possible to specify a pollution equation. Currently we are focusing only on the effect of the proxy vote variable on the toxic emissions of a firm. We include a lagged measure of proxy votes as an independent variable. This variable can potentially create sample selection bias. We have discussed this issue in detail under the econometric model section. Other independent variables in the pollution equation include firm characteristics (size, measured by the number of employees; sales growth SALESGROWTH, absolute and relative emissions; if it sells final good and concentration of the industry it operates in, HERFINDEX), regulatory conditions (measured by number of inspections EPAINSPECTIONS), state specific variables (STRICT, NREXPT, AVERAGEINCOME, EDUC, RIGHTTOWORK, LAWYERSPERCAP), presence of environmental groups (SIERRA), and industry effects. It is possible that larger firms measured by the number of employees might have higher emissions due to the scale of their operations. On the other hand, larger firms have deeper pockets and might be able to invest in pollution abatement technology. Sales growth variable, SALESGROWTH can also affect the modernity of a firm's abatement technology. Our EPAINSPECTIONS variable captures the effect of government regulatory activity. Finally, we account for the time effect by including year specific binary variables.

Econometric Model

Hypothesis V is tested by estimating the following equation:

$$Y_{it} = \gamma PV_{it-2} + \delta Z_{it} + u_i + \varepsilon_{it} \tag{2.14}$$

$$\varepsilon_{it} = \rho\varepsilon_{it-1} + e_{it} \tag{2.15}$$

where, Y_{it} is a measure of the ith firm's toxicity weighted emissions in time t. Z_{it} is a vector of exogenous explanatory variables that pertain to firms' characteristics. The indicator variable PV_{it-2} indicates if firm i was a target of a proxy vote in time period $t-2$. We have estimated equations 2.14 and 2.15 as both fixed effects and random effects model. In the fixed effects model u_i are assumed to be fixed parameters and could be related with the covariates. In the random effects model we maintain the assumption that u_i are independent of the other covariates. The disturbance term ε_{it} is assumed to be first order autoregressive. $|\rho| < 1$ and e_{it} is independently and identically distributed (i.i.d.). We tested for the presence of serial correlation by following the test specified in Wooldridge (2002)[27] and found evidence in favor of serial correlation. Hence, we specify disturbance term as autoregressive.

Proxy variable included in the pollution equation is lagged by two periods. We still consider the possibility that there may be sample selection bias. Due to unobservable variables, the firms that had a proxy vote against them may have been more likely to reduce their emissions even without a proxy vote against them.[28] In the presence of correlation between the error terms in proxy vote equation and pollution equation and no correction for sample selection, our estimates would be biased and inconsistent. We deal with this problem by implementing the procedure outlined by Vella (1998).[29] We correct for sample selection bias by including augmented inverse

[27]Following Wooldridge (2002) we interpret serial correlation in the errors of the panel data as error in each time period contains a time constant omitted factor. We have tested the null hypothesis of no serial correlation against the alternative that the error is first order autoregressive procedure. See Wooldridge (2002), page 176-177 for the details of the test.

[28]Heckman (1978) refers to this problem as "endogenous treatment problem" and it is closely related to the sample selection model (Vella 1998).

[29]We implement two of the procedures suggested by Vella (1998) to account for sample selection.

mills ratio in our pollution equation along with proxy vote variable. We corrected the standard errors by using Murphy-Topel correction. The procedure suggested by Vella (1998) also allows us to test for the presence of sample selection bias. We did not find any evidence of sample selection in our pollution equation. Hence, we have reported the results without sample selection correction. All time varying covariates other than the proxy vote variable are contemporaneous. The fixed effects model includes only time varying covariates. All state specific characteristics other than STRICT, NREXPT and SIC codes are excluded from the fixed effects model.

2.4 Data Description

Several different data sources are used to provide information on the variables used in this paper. In all the models estimated, our sample population of firms is the

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The first procedure involves estimating β by random effects probit and then constructing generalized inverse mills ratio given by:

$$IMR_{it} = PROXYVOTE_i[\frac{\phi(X_{it}\hat{\beta})}{\Phi(X_{it}\hat{\beta})}] + (1 - PROXYVOTE_i)[\frac{-\phi(X_{it}\hat{\beta})}{1 - \Phi(X_{it}\hat{\beta})}] \tag{2.16}$$

Where, X_{it} is a vector of explanatory variables that determine if a firm is chosen as a proxy vote target. The indicator variable $PROXYVOTE_i$ that indicates if a firm i is a target of a proxy vote in time period t and β is the estimated parameter vector. ϕ and Φ are respectively the pdf and cdf for normal distribution. In the next step we include this IMR and proxy vote variable in the pollution equation. The t-ratio on sample selection term (IMR) was insignificant in all the different specification, providing us with evidence that we do not have sample selection bias in our sample. Since the second equation included a predicted variable, our standard errors were inconsistent. We corrected the standard error in this case by using Murphy-Tope corrections. In all the specifications standard errors were larger after the correction. The second procedure also involves estimating the first equation by Probit (in our case Proxy vote equation by random effects probit) and then obtaining predicted residuals. In this case residuals are calculated the usual way. The predicted residuals are included in the second equation (here pollution equation) along with lagged proxy vote variable. The significance of residual parameter in the second stage tells us that there is sample selection bias. In our case we found residual parameter to be insignificant in all the models we estimated. Since the second equation includes a predicted variable, our standard errors are inconsistent. As mentioned earlier, Murphy-Topel correction can be used to correct the standard errors. We did not correct standard errors for this procedure. Since we found no evidence of sample selection by the first method as well, we believe we do not have sample selection bias in our equation. This procedure is also implemented by Sam & Innes (2008).

S&P 500. Firm level financial data such as sales, number of employees, total assets, gross assets, net income, and depreciation and amortization are collected from the Standard & Poor's Compustat database. Our dataset consists of only public firms as the financial data are available only for publicly held firms. Data on environment-related boycotts for the time period 1988-95 are collected from *National Boycott News*.[30] Investor Research Responsibility Center (IRRC) provided us with the data on environment-related proxy votes for the time period 1988-2006. In our analysis the boycott variable is created as a binary variable that takes the value of 1 if the firm was boycotted in the time period 1988-95.[31] The proxy vote variable is a yearly binary variable that takes value of 1 if the firm had a proxy vote against it in that year. Data on firm-level adoption of environmental management systems (EMS) is available for 1994 and 1995.[32] This data is obtained from a survey of S&P 500 firms conducted by the Investor Research Responsibility Center (IRRC) in 1994-95. In this survey, respondents indicate whether they have adopted each of a number of different environmental policies.

The data on ISO 14001 certification is provided by *QSU Publishing Company*.[33] QSU publishes a database of ISO 14001 registered companies. We have data for the time period 1996-2006. ISO 14001 was designed and developed in 1996 by the International Organization for Standardization (ISO).[34] The ISO 14001 standard is a part of ISO 14000[35] series, a family of environment management systems standards. ISO

[30]This publication was discontinued after 1995. We are thankful to Abdoul Sam for providing us with the data.

[31]We do not have exact information on start and end date for each boycott. Hence, it is not possible to determine the exact time period the firm was being boycotted.

[32]See Khanna & Anton (2002) and Anton et al. (2004) for details.

[33]http://www.qsuonline.com/

[34]ISO is the world's largest developer and publisher of International Standards. ISO organization promotes and designs voluntary international standards and it has developed more than 8000 of these standards (Szymanski & Tiwari 2004).

[35]ISO 14000 series consists of two kinds of standards. The first set is ISO 14001, which is a procedural standard. The second set of standards provide guidance to the managers in various

14001 is the only certifiable standard in this series. The main goal of ISO 14001 is to help businesses to reduce the environmental impact and to become more involved in proactive environmental management. This standard specifies a series of minimum requirements that must be met by the environmental management system of the company. After implementation, the company can obtain a certificate of compliance that recognizes that the EMS meets the established requirements (Gonzalez-Benito & Gonzalez-Benito 2008).

Data on air chemical releases[36] is obtained from Toxic Releases Inventory (TRI).[37] We have limited our attention to Clean Air Act (CAA) chemicals as the TRI list of reportable toxic chemicals varies from year to year. Addition of new chemicals or deletion of old chemicals can inflate or deflate the emissions from a facility. We have dealt with this problem by focusing on a fixed set of CAA chemicals. TRI database identifies each facility reporting to it by its name, location, primary standard industrial codes (SIC) codes and its parent company name.

Data on facility-level inspections under the CAA are collected from The Integrated Data for Enforcement Analysis (IDEA) database over the time period 1988-2003. EPA reports inspections conducted by state and EPA. We have constructed three different measures of inspections: inspections conducted by EPA, inspections conducted by state and total number of inspections conducted either by EPA or state. Full compliance evaluations (FCE) are classified as inspections.[38] The data provided by the TRI dataset and IDEA dataset is at the facility level but all other data is reported at parent company level. We obtained firm level emissions and inspections

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aspects of environment management, for example, ISO 14010 (Environmental Auditing) and ISO 14020 (Environmental Labeling).

[36]We have focused on air releases as they constitute the largest proportion of total releases

[37]http://www.epa.gov/enviro/html/tris/ez.html

[38]EPA credits Full Compliance Evaluations (FCE) as inspections and Partial Compliance Evaluations (PCE) not as inspections.

data by grouping the facilities by parent company name after merging TRI and IDEA dataset. We have accounted for variance in risks from exposure to different chemicals by creating a toxicity weighted measure of emissions. Data on toxicity weights is collected from EPA's Integrated Risk Information System (IRIS).[39]

We have state specific data on Sierra Club membership, state expenditures on natural resources and strict liability (binary variable) over the time period 1988-2003.[40] The Maxwell, Lyon and Hackett (2000) dataset provided additional information on state specific characteristics including, percentage of college degrees, lawyers per capita, and binary variables indicating if the state has a right to work statute, for 1988.[41] US Census Bureau provided information on state population density for years 1990 and 2000. State population density was used to calculate per capita Sierra club membership.

Our sample population of the firms is the S&P 500. The sample is further limited by availability of financial information. Merging the Compustat and environmental data set for these firms and after accounting for the availability of financial data we get a sample of total of 459 companies for the boycott equation and an unbalanced panel of 6580 firms for the proxy vote equation.[42] We have limited our sample to the

[39]http://www.epa.gov/iris. This dataset contains information on both Inhalation Unit Risk values for chemicals with carcinogenic effects and RfCs for chemicals with chronic, non-cancer health effects. The information provided in IRIS dataset is peer-reviewed and evaluated and accepted by all of EPA.

[40]Data on Sierra Club membership is provided by Sierra Club. We are thankful to Abdoul Sam for providing us with the data. Data on state expenditures in natural resources are collected from US Statistical Abstracts (several years) and data on strict liability are obtained from Environmental Law Institute. We are thankful to Santiago Guerrero for providing us with data on these two variables.

[41]We have used 1988 values for state specific characteristics as these state level characteristics are not expected to change significantly overtime.

[42]For the boycott equation we consider the firms that are S&P 500 in December 1995 and for the proxy vote equation the firms that are S&P 500 in January 2003. We adopted this method to take into account the fact that the sample of S&P firms changes overtime. The sample for proxy vote equation covers the time period 1989-2003. Time period for estimation is defined on the basis of data availability of all the important variables.

time period 1996-2003 for ISO 14001 equation.[43] This restricted time period gives us a sample of 2844 firms. Tables 2.1 to 2.3 report the variable definitions and summary statistics. Table 2.2 presents the summary statistics for the cross sectional and panel variables. These summary statistics show that about five percent of the firms in our sample were boycotted and about seven percent had a proxy vote against them. We can also observe that 44 percent of the firms adopt EMS. This percentage is much higher than the percentage of ISO 14001 certifications that stand at seven percent at the end of 2003.[44] Table 2.3 compares the summary statistics for boycotted and non-boycotted firms in Panel A. In Panel B we compare the characteristics of firms with a proxy vote against it and firms with no proxy vote against it and in Panel C we compare the characteristics of EMS adopters and non-EMS adopters. Panel A of Table 2.3 shows that the boycotted firms are bigger (measured by sales and number of employees), have larger absolute and relative emissions and are located in states with higher Sierra club membership. Test of means reported in Panel B shows that firms with proxy vote against them are significantly different from firms with no proxy votes against them in terms of size, emissions, inspections and expenditure on natural resources. A firm with a proxy vote against is typically bigger, a heavy emitter and also more frequently inspected. Comparison of EMS adopters and non-adopters in Panel C reveals that EMS adopting firms are larger in size, have higher emissions (relative and absolute) and higher inspections as compared to EMS non-adopters. EMS adopters are also located in states with larger environmental constituencies, measured by Sierra club membership.

[43]This time period is defined on the basis of availability of data on ISO 14001 certification and other important variables. ISO 14001 registrations started in 1996. This gives us 1996 as the start year and data on state specific variables is available till 2003. Hence, we have limited our sample to the time period 1996-2003.

[44]Notice that our sample for ISO 14001 certifications is a right censored sample as mentioned earlier. It is possible that by 2008 number of ISO certified firms increased substantially.

2.5 Results

2.5.1 Boycott Equation

Table 2.4 presents the results from probit estimation of the boycott equation. Model I is a parsimonious specification including only the number of employees (NOEMPLOYEES) working for a firm in year 1988 and industry specific effects. We control for industry specific effects by including indicator variables for the heavily represented SIC codes.[45] NOEMPLOYEES is a proxy for size of the firm and is expected to be the one of the most important factors that determines if a firm is a good target for boycott. SALES variable can also act as a proxy for the size of the firm. All the models were also estimated using SALES as a regressor instead of number of employees of a firm. Our results are similar in both the cases. We chose to present the results with NOEMPLOYEES variable. The second specification includes more firm specific variables: if it sells a final good, its emissions relative to the industry and absolute emissions along with SIC codes. The third model includes per-capita Sierra club membership and other state specific variables.

Our estimation results show that the NOEMPLOYEES88 variable is statistically significant in all the specifications. Addition of other correlates does not weaken the effect of NOEMPLOYEES88 on the probability of boycott. We also notice that the number of employees variable is positively related to the probability of boycott. As expected, larger firms make better targets for a boycott. We evaluated the marginal effect of NOEMPLOYEES88 on boycott variable at the sample means. We find that in all the three specifications the estimated marginal effect of NOEMPLOYEES88 on the probability of boycott is about 0.0002. In other words, a one percent increase in

[45] The sample contains fifty-three two-digit SIC codes. We have chosen to control for only those SIC codes that have at least five percent observations under it. During estimation some of these SIC codes became collinear with the outcome and were dropped.

NOEMPLOYEES88 would increase the boycott rate by 0.02 percent. We also find that the firms operating in the states with larger per-capita Sierra club membership are more likely to become the target of a boycott. SIERRA88 variable increases the probability of a boycott by 1.5 percent. Though this variable is significant only at the 5 percent level of significance, its marginal effect is bigger than that NOEMPLOYEES88. We find that the proximity to the consumers is an important element to determine the possibility of a firm being boycotted. The probability of being boycotted increases by about 4 percent if product goes from not being a final product to being a final product. We also find that the relative emissions of a firm are positively related to the probability of being boycotted. RELEMISSIONS89 measure the emissions of a firm relative to the industry emissions.[46] We do not find that any other state variables to be significant and no evidence of significant industry effects.[47]

2.5.2 Proxy Vote Equation

Estimation results from the proxy vote equation are presented in Table 2.5. As in the case of boycott equation, we present results from three different specifications. Since we have information on proxy votes against a firm for each year, proxy vote equation is estimated by random effects probit model. Our results reveal the significance of the size of a firm in determining whether the firm will become the target of an activist

[46] As mentioned earlier we have used air releases data for 1989 instead of year 1988. This is done to minimize any data reporting problems. EPA reported air releases data for the first time in year 1988, hence this year's data might suffer from reporting problems. A measure of industrial emissions is constructed at 1 digit SIC code. This gives us RELEMISISONS as firm releases/industry releases. These emissions are toxicity weighted and normalized by the sales in the firm and in the industry.

[47] Our boycott equation focuses only on environmental (and animals issues related) boycotts. We estimated a similar boycott equation with boycotts focusing on other issues like human rights violation, violence on TV etc. For these boycotts we expected the size of the firm to be the main determinant of whether a firm will become target of a boycott. We did not expect to see that Sierra club membership and emissions playing any part in predicting these boycotts. Estimation results reported in Table A-4 confirmed our expectations. We find that the only variable that is significant is the size of the firm. This result confirmed that these other boycotts are different in character from environmental (and animal issues related) boycotts.

campaign. NOEMPLOYEES variable is significant in all the three models at one percent level of significance. Size of a firm plays an important part in determining whether a firm will be boycotted or will become target of a proxy vote. However, the motivation is different in these two campaigns. The importance of NOEMPLOYEES variable in boycott equation can be explained by the fact that bigger firms tend to get more publicity when they are boycotted and in the process generate awareness about the issue at stake. This negative publicity can also act as a deterrent for other firms engaged in similar activities. However, similar motives cannot explain the significance of NOEMPLOYEES variable in the proxy vote equation. It is our conjecture that larger firms are targeted for proxy votes as stake holders might believe that the changes in environmentally detrimental activities of larger firms would have larger impact on the environment. These firms could also set an example for other firms to follow. Our results are robust to the inclusion of sales which measure the size of the firm.

We find that the final good indicator variable is significant in all the three models. We get the same result as in the boycott equation that the proximity to final consumers increases the probability of a proxy vote against the firm. We also find that inclusion of time effects does not change our results. We find that toxic releases by the firm and inspections against the firm positively affect the probability of proxy vote. However, we do not find that the Sierra club membership plays any part in identifying a firm as a possible target. This result can be explained in terms of the dissimilar nature of the two activist campaigns: boycotts and proxy votes. Boycotts are a public way of demonstrating displeasure towards the practices of a firm. Proxy votes are used as a means by the stake holders to compel the firms to behave in a sensitive way towards the environment. High releases and particularly inspections are an indicator that the firm is in trouble. Stake holders could react to this information by bringing in proxy votes against the firm. In case of boycotts, the boycott organizing agency has to pick an issue that resonates with the public and also the issue has to be narrow enough that it can be associated with a certain firm (Friedman 1999). Hence, it might be better to choose an issue like destroying old age forests (that could be specific to a firm) instead of high toxic releases. This result also partially refutes the hypothesis by Baron (2006) that states that socially responsible firms are more likely to be targeted by the activist campaigns as they have much more at stake in terms of their reputation and hence are more likely to concede.

We have used random effects probit model for estimation of proxy vote equation. This model is estimated by quadrature method. This method could be sensitive to the number of "support points" chosen. We have tested for the stability of results by evaluating the likelihood function for estimation of random effects probit at different "support points": 8, 12 and 16. The results are presented in the Table A-5 in appendix. We can observe that the value of likelihood function does vary significantly due to the choice of number of "support points". We have also tested for the presence of random unobserved effect. This effect is tested by testing the null hypothesis $\rho = 0$. This test compares the pooled estimator with the panel estimator. The third last row of the Table 2.5 reports the value of rho. The p-value shows that we reject the null hypothesis in all the three models. This shows that the panel-level variance component is important and the panel estimator is different from the pooled probit estimator in all the cases.

2.5.3 EMS Adoption Equation

We estimated the EMS adoption equation and boycott equation jointly by bivariate probit to account for correlation among the error terms. The p-value indicated that we fail to reject the null of no correlation between the error terms. We estimated several different specifications and arrived at the same conclusion. Lack of correlation between the error terms allows us to estimate both the equations separately using probit maximum likelihood estimation procedure. We have not re-estimated the boycott equation as the results are reported in the Table 2.4. We test for any potential effect of boycott against a firm on its decision to adopt EMS by including boycott variable as a regressor. The estimation results are presented in the Table 2.6. We find that the coefficient on boycott variable is positive and significant in all the three models. This result provides us evidence in favor of our main hypothesis that boycotts spur EMS adoption. This variable is also significant in terms of magnitude. We estimate that boycott against a firm increased the probability of EMS adoption between 27 and 32 percent.

Our estimation results for EMS equation support our conjecture that the bigger firms are more likely to adopt EMS. Larger firms, as measured by the number of employees, have more resources and hence can invest in developing new technologies or implementing existing technologies. We can also measure the resources at a firm's disposal based on firm's total assets (TASSETS). However, we find mixed results for this variable. In model II this variable is positively related to EMS adoption but in model III it is negatively related to EMS adoption. As total assets act as a measure of size and resources of the firm, this result is puzzling. We also found evidence that firms with large relative and absolute toxic releases.[48] and higher number of inspections are more likely to adopt EMS. All these variables are positively related to the probability of EMS adoption.[49] Anton et al. (2004) found similar result for the emissions but they did not find the effect of the number of inspections on EMS adoption to

[48]Our sample contains several firms with zero emissions; we have not excluded them from our sample as about fourteen percent of EMS adopters have zero emissions.

[49]We wanted to test if the R&D of a firm plays a part in EMS adoption. We estimated the EMS equation with R&D as a regressor. However, the data on R&D expenditures of a firm are sparse and it reduced our sample size by half. We did not find R&D variable to be significant in any of the specifications. Hence, we excluded R&D variable from our estimations.

be statistically significant. They noted that large emitters might adopt EMS in order to generate cost savings by adoption of proactive environmental management. The positive impact of inspections in our estimations might suggest that EMS might be adopted to obtain leniency from the regulators or that the firms with a track record of bad environmental performance use EMS adoption as a means to improve their image. We also find that STRICT has a significant negative effect on probability of EMS adoption. As mentioned by Sam & Innes (2008) this could be due to the fact that strict liability promotes an adversarial mentality towards pollution control that is not supported by the philosophy of EMS adoption. We also find that FINALGOOD negatively affects the probability of EMS adoption. This variable reduces the probability of EMS adoption by about 15 percent. This result is counterintuitive as we expected that proximity to consumers will influence the probability of EMS adoption positively.[50]

We tested for the effect of proxy votes on EMS adoption by including proxy vote as a covariate in EMS adoption equation.[51] Results from the estimation are reported in the Table 2.7.[52] We find proxy vote variable to be positively related to EMS adoption in all the three models and significant in two models out of three models. The effect of a proxy vote on the probability of EMS adoption varies between 14 to 30 percent. Though proxy vote variable becomes statistically insignificant after controlling for toxic releases and prior inspections in model III, it still is an economically significant

[50]Our result is contrary to the one reported by Anton et al. (2004) and several other studies. All these papers report that consumer pressure has direct impact on a firm's management strategies. Firms with closer contact with consumers are expected to be more environmentally proactive.

[51]We also considered the case where we included both boycott and proxy vote variable in the same EMS adoption. We have reported the results from this regression in Appendix A Table A-6. We find that the proxy vote variable is significant in Models I and II. Proxy vote variable becomes insignificant after the inclusion of environmental performance variables: emissions and inspections.

[52]As in the case of boycott equation and EMS adoption equation, we considered the possibility that errors might be correlated for proxy vote equation and EMS adoption equation. We estimated EMS equation and proxy vote equations jointly by bivariate probit. Lack of correlation between the error terms allowed us to estimate each equation separately as probit model.

variable. It increases the probability of EMS adoption by about 14 percent. All other results for EMS adoption are similar to EMS adoption equation with boycott variable as a regressor.

2.5.4 ISO 14001 Registration Equation

Next we analyze the impact of proxy votes against a firm on ISO 14001 registrations. As discussed earlier, given the unique nature of the ISO 14001 variable, we have estimated hazard models to understand the determinants of ISO 14001 adoption. We have reported results from exponential hazard model in the Table 2.8 and estimation results from more general Cox model in the Table 2.9.[53] We have estimated three sets of models in both the cases. Model I covers the entire time period; model II is estimated for years 1996-99 and model III for years 2000-2003. The models are split in two time periods to take into account increased ISO 14001 certifications year 2000 onwards. In our sample, out of total registrations, about 73 percent of registrations occurred between 2000 and 2003 as opposed to only 27 percent between 1996 and 1999. In order to test our conjecture that hazard rate would differ in time period before and after 2000, we estimated Model I in the Table 2.8 as a piecewise-constant exponential hazard rate model. This model allows the constant rate to vary within pre-defined time-segments. We found both PERIOD variables to be significant indicating that the hazard rate is different in these two time periods. This result motivated us to split the study period in two and re-estimate the models to analyze if there is any difference in the effect of proxy vote variable on early and late ISO 14001 adoptions.

[53] We estimated exponential hazard model without time pieces. Our results do not change. All our results are robust to specifying Weibull as the underlying distribution instead of exponential. We have reported results from exponential model as it is relatively easy to estimate models with time piece when the underlying distribution is exponential. We also included a variable indicating if the firm was subjected to a proxy vote in the time period 1988-95. We did not find this variable to be significant in any of the models and hence we omitted it from the final analysis.

A hazard ratio of greater than one indicates a positive relationship and hazard ratio below one indicates negative relationship.[54] We find proxy vote variable to be positively related to the probability of ISO 14001 registration in all the three specifications for both exponential and Cox models. We start by discussing the results for Model I for both exponential and Cox model. Our results are robust in terms of significance across exponential and Cox models. We find that the proxy vote against a firm increased the likelihood of ISO 14001 registration by about 93 to 98 percent as compared to the case when there is no proxy vote. Company size, measured by the number of employees turns out to a significant variable positively related to ISO 14001 registration. This finding is similar to the one reported by Gonzalez-Benito & Gonzalez-Benito (2005) and Nakamura et al. (2001). This result emphasizes that the greater availability of resources to larger companies is a determining factor for initiating ISO 14001 certification. This certification involves significant fixed costs. According to Delmas (2000) total cost of implementing and maintaining the system could be as high as $100,000 per year. These costs are more significant for the smaller firms than for larger ones. Larger organization may put to use already existing skills and facilitate formulation of environmental policies and integrate them into organizational policies.

Firms with higher emissions had lower propensity to certify. This result casts doubt on the view that certification can act as a signal. This fact is at odds with the result that firms that receive more regulatory inspections are significantly more likely to join ISO 14001. This is a reflection of the fact that firms attempt to fight regulatory pressures by asserting their commitment to the environment through ISO 14001

[54]Interpretation of hazard ratios differs from that of linear parameter estimates. There is a difference in interpretation based on if we are looking at a continuous or a discrete (binary) explanatory variable. For example, a hazard ratio of 0.2 for a binary variable means that group 1 has 80% smaller hazard than the reference category. A hazard ratio of 1.4 implies that group 1 has 40% higher hazard than the reference category. If hazard ratio is 1.71 for a continuous variable, it indicates that one unit increase in continuous variable increases the hazard rate of outcome by 1.17.

registration and hence treat it as a signal of superior environmental performance.[55] It is possible that firms that are heavy polluters need to go through intensive environmental planning and policy formation before seeking the certification and time and costs of this process act as a deterrent.[56] We find several state specific characteristics to be significant. Firms located in states with more educated residents are more likely to adopt ISO 14001. Potoski & Prakash (2005) find similar result and conjecture that this might be because ISO 14001 reputation is more valuable to the firms if local residents are better equipped to detect and process the information or more educated residents have higher demand for environmental performance. States with right to work statute and higher number of lawyers per capita are less likely to join ISO 14001.

The key finding from models II and III is that proxy votes play a significant role in early ISO 14001 registrations. The hazard ratio indicates that early adopters are four times more likely to certify to ISO 14001 if they had a proxy vote against them. This effect is significantly larger than the overall effect of 93 percent. The impact of proxy votes is statistically insignificant for late adopters and increases the likelihood of adoption by only 34 percent. An explanation for significant effect of proxy votes on early adoption is that proxy vote against a firm provides the extra nudge that a firm need to certify to ISO 14001 early on. However, once the program becomes popular, other factors like adoption by peers and success of the program might be more important for certification than shareholder pressure. Most of our results in the models II and III are similar to the ones in Model I. Additionally, in model II we find that the states with strict liability statute have 85 percent less hazard of adoption of ISO 14001. Presence of strict liability statute makes parties responsible for any

[55] This result is similar to the one we found in case of EMS adoption equation. In this case signal is even stronger as ISO 14001 involves substantial cost outlays and third party auditing and certification.

[56] King et al. (2005) support the result with respect to emissions. Potoski & Prakash (2005) find evidence in favor of result about regulatory pressures. None of the papers find both the results together.

environmental damages and imposes significant cost on the firms. In this setup firms might decide not to join ISO 14001 and further increase their costs as certifying to ISO 14001 requires significant expenses. As in case of EMS adoption equation, we find counterintuitive result that firms with proximity to consumers are less likely to certify to ISO 14001.

2.5.5 Pollution Equation

The next question we examine is whether a proxy vote against a firm improves its environmental performance measured by the toxic releases of the firm. In order to test the robustness of our results, we estimated a number of specifications with different sets of explanatory variables.[57] The results from the pollution equation are reported in the Table 2.10. We have assumed the disturbance term to be first order autoregressive.[58] We have reported results from two representative models.[59] Our most notable result is that the coefficient on the lagged proxy vote variable is statistically significant in both the models and lead to reduction in the toxic releases of a firm. This result confirms our hypothesis that *proxy votes improve a firm's environmental performance*. The random effects model shows that the proxy vote against a firm reduces firm's emissions by 1.0 percent as compared to prior releases. We find similar result with fixed effects estimates that proxy vote leads to a reduction of 0.2 percent

[57]We estimated a wide variety of models with different specification. We obtained similar results for key variable of interest. Specifically, we get the result that the proxy vote variable is significant and has the expected positive sign in all the specifications. The level of significance varied over the different specifications. We also estimated pollution equation with lagged inspections and number of employees. Our results are same as the ones reported in the Table 2.10. All the models were estimated with fixed effects and random effects.

[58]We tested for autocorrelation in the both static and dynamic models. We found evidence of autocorrelation in both the models. We are currently in the process of estimating a dynamic pollution equation.

[59]We employed the procedure outlined in Vella (1998) and discussed earlier in this paper to correct for sample selection. The coefficient on the augmented inverse mills ratio was insignificant in all the models indicating no sample selection. Hence, we have omitted IMR from our models and reported results without it.

in the releases of a firm as compared to prior average releases.

In random effects model we find that the bigger firms (measured by larger number of employees) and states with higher per capita income have higher toxic releases.[60] An increase of about 1 percent in the size of the firm would increase toxic emissions by about 23 percent. Additionally, we find that the presence of a strict liability statute and higher number of lawyers per capita leads to a reduction in toxic releases. Negative coefficient on lawyers per capita variable indicates that states with higher possibility of litigiousness have lower emissions. According to random effects model strict liability statute decreases the emissions by 38 percent. This effect is lower in case of fixed effects model and stands at 17 percent. In random effects, model we find the noticeable result that consumer pressure does lead to a reduction in toxic emissions as indicated by the negative sign on FINALGOOD variable. Firms that have proximity to consumers reduce their emissions by about 11 percent as compared to prior average. We find no significant effects of inspections against the firm and the concentration of the industry in any of the models. Sierra club membership has the expected negative sign indicating that the firms will lower their emissions in environmental constituencies due to the fear of regulation. However, this variable is insignificant in both the models.

2.6 Concluding Remarks

Despite pervasiveness of activist campaigns like boycotts and a growing theoretical interest in the economics of activist campaigns, thus far, there is scarce empirical literature that studies these activist campaigns. In particular, there is no empirical

[60] We find similar result in case of fixed effects model as well. This result refutes the premise that environmental performance is a luxury good. That is, higher income constituencies would demand lower emissions. However, if we do not control for year effects, we find that this variable has expected negative sign in all the models.

evidence on the environmental impact of these activist campaigns. In this paper, we address this shortcoming by studying the process of target selection by activist campaigns. We identify major factors that determine whether a firm is chosen as a target by activist campaigns. We also test the impact of activist campaigns on environmental performance of the firm. We focus on two kinds of campaigns: boycotts and proxy votes. Though these two campaigns are significantly different from each other in their manner of operation, they share the common goal of - protecting the environment, by keeping an eye on corporate practices. Boycotts put external pressure on a firm through public action and proxy votes exert internal pressure on firms asking them to behave in a socially responsible way. We estimate several equations in order to examine: (1) the factors that determine whether a firm becomes a target of an activist campaign (proxy vote and boycott equations); (2) if a firm's adoption of an EMS is affected by a boycott or a proxy vote (EMS adoption equation); (3) impact of proxy votes on ISO 14001 certification; and (4) role played by proxy votes in reduction of toxic releases by a firm.

Theory suggests that a firm is more likely to be targeted by an activist campaign when the campaign is more likely to be successful/effective. For example, Baron (2001, 2006) argues that interest groups are more likely to choose "soft targets" (progressive firms), and to launch campaigns when the issue is more salient (with stronger environmental constituency) and the target is more susceptible to consumer pressure. In our preliminary work, we find evidence that these targeting criteria (as interpreted) are being applied in practice. Perhaps more importantly - and surprisingly - we find that, despite evidence of "soft targets," boycotts have had a significant effect in spurring rather coarse environmental practices, namely, the adoption of environmental management systems and ISO 14001 certification. Our estimation results indicate that a larger and hence more visible firm has a higher probability of being targeted for an activist campaign. Firms located in large environmental constituencies have a higher probability of becoming target of a boycott. “Dirty firms” (large relative or absolute emissions, high level of regulatory scrutiny) are also more likely to become target of an activist campaign. Our analysis provides evidence that activist campaigns can compel firms to take proactive environmental measures. We demonstrate that the activist campaigns can be instrumental in the adoption of EMS and ISO 14001. Boycott against a firm increased the probability of EMS adoption by 27-32 percent. We find similar support for our hypothesis that proxy votes spur EMS adoption. We also find evidence that proxy votes play a significant role in ISO 14001 certification and reduction of toxic releases of a firm. The early adopters of ISO 14001 are four times more likely to certify to ISO 14001 if they had a proxy vote against them.

Currently, we are in the process of estimating a dynamic pollution equation, and identifying a technique to test and correct for endogeneity in case of hazard models. Our future research will focus on the link between private politics and enforcement activity by the government. We plan to analyze if these campaigns act as compliment or a substitute to the enforcement activity by the government. Estimation of inspection and enforcement equations will help us to determine if the activist campaigns result in tightening of government regulation.

So far the common perception has been that activist campaigns have only limited usefulness. Our findings challenge this theory. Overall, this paper confirms the importance of activist campaigns in regulating firms’ behavior. Activist campaigns can act as a powerful weapon for promoting corporations to work towards better goals and practices. It also establishes that these campaigns can go a long way in improving the environmental performance of the firms. The results of this paper have important consequences for strategy formulation for activist campaigns and also for the firms in order to counter these pressures.

Table 2.1: Description of Variables

Variable Name	**Variable Definition**
BOYCOTT	Binary = 1 if the firm is boycotted in years 1988-95; 0 otherwise
EMS	Binary = 1 if the firm adopts EMS in years 1991-95; 0 otherwise
PROXYVOTE	Binary = 1 if the firm has a proxy vote against it in a particular year; 0 otherwise (annual)
PROXYVC	Binary = 1 if the firm has a proxy vote against it in years 1988-91; 0 otherwise (annual)
LAG2PROXYVOTE	Twice lagged proxy votes
$SIERRA_t$	Sierra club per-capita membership in firm's home state in year t
SIERRA	Sierra club per-capita membership in firm's home state
EDUC	Percentage of college degrees in firm home state, 1988
AVGERAGEINCOME	Average income in firms home state, 1988
SPENDAIRQUA	State expenditures on air quality programs in firms home state, 1988
STRICT	Binary = 1 if firm's home state has a strict liability statute, Annual
LAWYERSPERCAP	Number of lawyers per capita in firm home state, 1988
RIGHTTOWORK	Binary = 1 if firm's home state has a right-to-work statute, 1988
FINALGOOD	Binary = 1 if firm sells a final product; 0 otherwise
NREXPT	State Expenditures in Natural Resources (trillions of dollars), annual
HERFINDEX	Herfindahl index for firms three digit SIC codes
$SALES_t$	Sales of a firm (1000s) in year t
SALES	Sales of a firm (1000s) (annual)
$NOEMPLOYEES_t$	Number of firm employees (1000s) in year t
NOEMLOYEES	Number of firm employees (1000s) (annual)
TOTALASSETS	Total assets of the firm in year t
$TOTALASSETS_t$	Total assets of the firm (annual)
CAAEMISSIONS	Total firm emissions of CAA chemicals (millions of pounds), annual (Toxicity weighted)
$CAAEMISSIONS_t$	Total firm emissions of CAA chemicals (millions of pounds), in year t (Toxicity weighted)
RELEMISSIONS	Emissions relative to industry, annual
RELEMISSIONS$_t$	Emissions relative to industry in year t

Table 2.1: Description of Variables

Variable Name	**Variable Definition**
EPAINSPECTIONS	Total number of inspections against a firm, annual
$EPAINSPECTIONS_t$	Total number of inspections against a firm in year t
SALESGROWTH	Firm percentage sales growth (annual)
SICNUM	Binary = 1 if SIC code is equal to "NUM"; 0 otherwise

Table 2.2: Descriptive Statistics of Variables

Variable Name	Mean	Standard Deviation
Cross-sectional Variables		
BOYCOTT	0.048	0.214
EMS	0.447	0.498
PROXYVCS	0.094	0.292
SALES88	5.774	10.605
SALES89	6.3	11.231
NOEMPLOYEES88	36.776	63.39
NOEMPLOYEES89	37.807	63.143
TOTALASSETS88	0.104	0.446
TOTALASSETS89	0.155	0.212
CAAEMISSIONS89	1.502	4.369
RELEMISSIONS89	0.015	0.083
EPAINSPECTIONS88	3.789	9.672
EPAINSPECTIONS89	3.466	8.736
SIERRA88	2.264	1.484
SIERRA89	2.417	1.567
EDUC	20.897	3.439
AVERAGEINCOME	0.152	0.024
SPENDAIRQUA	1.265	0.742
STRICT	0.736	0.441
LAWYERSPERCAP	3.219	1.012
RIGHTTOWORK	0.305	0.461
FINALGOOD	0.359	0.48
Panel Variables		
PROXYVOTE	0.065	0.246
ISO	0.072	0.259
SALES	8.543	16.8
NOEMPLOYEES	37.59	72.59
SIERRA	2.843	0.499
TOTALASSETS	0.202	0.606
CAAEMISSIONS	0.683	2.781
RELEMISSIONS	4.213	142.7
EPAINSPECTIONS	4.312	11.91
STRICT	0.851	0.356

Table 2.2: Descriptive Statistics of Variables

Variable Name	**Mean**	**Standard Deviation**
NREXPT	0.578	0.639
SALESGROWTH	0.176	0.936
AVERAGEINCOME	0.025	0.004
HERFINDEX	0.151	0.148

Notes:
- STRICT, FINALGOOD, PROXYVOTE, PROXYVCS, EMS, BOYCOTT, RIGHTTOWORK are binary variables.
- EDUC, LAWYERSPERCAP, RIGHTTOWORK, AVERAGEINCOME, STRICT, SPENDAIRQUA listed under cross-sectional variables are measured in 1988.
- Panel covers the time period 1989-2003.
- ISO variable is measured over the time period 1996-2003 as ISO 14001 certification started in 1996.

Table 2.3. Summary Statistics

PANEL A	**Boycotted Firms**		**Non-Boycotted Firms**		**Test of**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Means**
SALES88	15.74	26.18	5.27	8.94	-1.87*
NOEMPLOYEES88	91.16	164.66	34.04	52.52	-4.20***
CAAEMISSIONS89	3.18	6.6	1.42	4.22	-1.86*
RELEMISSIONS89	0.07	0.23	0.01	0.07	-3.46***
SIERRA88	2.82	1.79	2.24	1.46	-1.80*
N = 459	22		437		
PANEL B	**Proxy Vote**		**No Proxy Vote**		**Test of**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Means**
SALES	27.41	38.91	7.23	13.06	-10.67***
NOEMPLOYEES	98.79	157.72	33.35	60.29	-8.53***
CAAEMISSIONS	1.91	4.57	0.59	2.59	-5.88***
RELEMISSIONS	1.52	4.97	4.4	147.63	1.51
EPAINSPECTIONS	14.76	22.35	3.59	0.13	-10.25***
SIERRA	2.59	0.44	2.86	0.5	1.19
NREXPT	0.49	0.56	0.58	0.64	3.20**
N = 6580	427		6153		
PANEL C	**EMS Adopter**		**Non-EMS Adopter**		**Test of**
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Means**
SALES89	7.62	14.52	5.24	7.48	-2.13**
NOEMPLOYEES89	44.53	74.44	32.38	53.98	-1.95*
CAAEMISSIONS89	3.22	6.06	0.11	0.79	-7.29***
RELEMISSIONS89	3.03	8.56	0.17	1.21	-4.75***
EPAINSPECTIONS89	6.27	11.1	1.2	5.23	-6.03***
TOTALASSETS89	8.41	24.72	8.41	20.76	2.53**
SIERRA89	2.82	1.79	2.24	1.46	-1.80*
N = 459	205		254		

Table 2.4: Estimation Results for Boycott Equation: Probit Models

Variable Name	**Model I**	**Model II**	**Model III**
NOEMPLOYEES88	0.0003***	0.0002**	0.0002***
	(0.000)	(0.000)	(0.000)
FINALGOOD (Firm sells final product)		0.047**	0.040**
		(0.024)	(0.022)
RELEMISSIONS89 (CAA emissions relative to industry)		0.136*	0.121*
		(0.081)	(0.068)
CAAEMISSIONS89		0.001	0.001
		(0.002)	(0.002)
SIERRA88			0.015**
			(0.006)
STRICT			-0.004
			(0.024)
SPENDAIRQUA (State spending on air quality programs)			-0.028
			(0.017)
EDUC			0.004
			(0.006)
LAWYERSPERCAP			-0.008
			(0.020)
RIGHTTOWORK (State has right to work statute)			0.004
			(0.030)
AVERAGEINCOME			-0.051
			(0.959)
SIC28	0.045	0.051	0.060
	(0.049)	(0.052)	(0.055)
SIC35	-0.140	-0.009	-0.012
	(0.031)	(0.032)	(0.024)
SIC38	0.006	0.035	0.024
	(0.051)	(0.070)	(0.056)
SIC60	-0.008	-0.019	-0.015
	(0.036)	(0.025)	(0.019)
Intercept	-1.854	-2.111	-3.043
	(0.141)	(0.190)	(1.310)

Table 2.4: Estimation Results for Boycott Equation: Probit Models

Variable Name	Model I	Model II	Model III
Log-Likelihood	-83.156	-79.094	-73.156
Chi-sq	10.29	18.41	30.29
(p-value)	(0.0674)	(0.018)	(0.017)
N	459	459	459

Notes: Dependent Variable for this equation is boycott variable (binary).

Marginal effects are reported here and standard errors are reported in parenthesis.

For the intercept term we have reported the parameter estimate.

*** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.5: Estimation Results for the Proxy Vote Equation: Random Effects Probit Models

Variable Name	Model I	Model II	Model III
NOEMPLOYEES	0.115***	0.112***	0.116***
	(0.020)	(0.020)	(0.021)
FINALGOOD (Firm sells final product)	0.213***	0.184***	0.149**
	(0.050)	(0.050)	(0.053)
CAAEMISSIONS	0.021***	0.027***	0.040***
	(0.008)	(0.007)	(0.009)
RELEMISSIONS (CAA emissions relative to industry)	-0.016	-0.018	-0.022
	(0.025)	(0.094)	(0.030)
EPAINSPECTIONS	0.067***	0.063***	0.059***
	(0.013)	(0.014)	(0.014)
HERFINDEX (Herfindahl index, 3 digit SIC)	0.058	0.061	0.034
	(0.056)	(0.058)	(0.057)
SIERRA		0.017	0.041
		(0.023)	(0.025)
STRICT (State has strict liability statute)		0.197**	0.093
		(0.120)	(0.139)
NREXPT (State spending on natural resources)		-0.019	-0.058
		(0.057)	(0.064)
EDUC		-0.175	-0.035
		(0.534)	(0.555)
LAWYERSPERCAP		-0.067	0.171
		(0.369)	(0.398)
RIGHTTOWORK (State has right to work statute)		0.048	0.016
		(0.048)	(0.051)
AVERAGEINCOME		1.393***	0.086
		(0.202)	(0.769)
SIC28	0.025	0.021	0.022
	(0.017)	(0.017)	(0.018)
SIC35	0.007	0.004	-0.004
	(0.015)	(0.016)	(0.016)
SIC36	0.000	-0.002	-0.005

Table 2.5: Estimation Results for the Proxy Vote Equation: Random Effects Probit Models

Variable Name	Model I	Model II	Model III
	0.020)	(0.020)	(0.021)
SIC37	0.019*	0.020*	0.019
	(0.011)	(0.012)	(0.012)
SIC38	0.017	0.011	0.011
	(0.013)	(0.014)	(0.015)
SIC49	0.051***	0.052***	0.047**
	(0.018)	(0.018)	(0.019)
SIC60	-0.096***	-0.094***	-0.099***
	(0.033)	(0.034)	(0.036)
SIC63	-0.013	-0.016	-0.014
	(0.015)	(0.015)	(0.016)
SIC73	-0.069***	-0.071***	-0.073***
	(0.026)	(0.027)	(0.028)
Intercept	-2.727	-4.106	-5.402
	(0.158)	(0.466)	(0.885)
Time Effects	NO	NO	YES
Log-Likelihood	-1203.11	-1194.59	-1142.12
Chi-sq	130.47	143.42	188.38
(p-value)	(0.000)	(0.000)	(0.000)
rho	0.446	0.454	0.469
(p-value)	(0.000)	(0.000)	(0.000)
N	6580	6580	6580

Notes:

- Dependent Variable for this equation is proxy vote variable (binary).

- We report standard errors in parenthesis.

- *** significant at 1%, ** significant at 5%, * significant at 10%.

- We conduct the test of pooled estimator vs. the panel estimator.

We reject the null of rho = 0 in all the three models. The rejection of null hypothesis shows that the panel-level variance component is important and panel estimator is more appropriate in this case.

Table 2.6: Determinants of Adoption of EMS System (with Boycott Variable): Probit Models

Variable Name	Model I	Model II	Model III
BOYCOTT	0.265***	0.288**	0.320**
	(0.108)	(0.129)	(0.127)
NOEMPLOYEES89		0.001**	0.003**
		(0.001)	(0.001)
FINALGOOD (Firm sells final product)		-0.154**	-0.65
		(0.062)	(0.115)
CAAEMISSIONS89		0.086***	0.080***
		(0.031)	(0.032)
RELEMISSIONS89 (CAA emissions relative to industry)		0.028*	0.028*
		(0.016)	(0.015)
EPAINSPECTIONS89		0.019***	0.020***
		(0.006)	(0.006)
TOTALASSETS89		0.009***	-0.010***
		(0.003)	(0.003)
SIERRA89			-0.025
			(0.027)
STRICT (State has strict liability statute)			-0.168*
			(0.101)
SPENDAIRQUA (State spending on air quality programs)			0.07
			(0.056)
EDUC			0.024
			(0.020)
LAWYERSPERCAP			-0.135*
			(0.078)
RIGHTTOWORK (State has right to work statute)			-0.106
			(0.089)
SIERRA*FINALGOOD			-0.044
			(0.042)
STRICT*NOEMPLOYEES			-0.002
			(0.001)
SIC28	0.516***	0.471***	0.488***
	(0.059)	(0.107)	(0.110)

Table 2.6: Determinants of Adoption of EMS System (with Boycott Variable): Probit Models

Variable Name	**Model I**	**Model II**	**Model III**
SIC37	0.281***	-0.004	0.022
	(0.094)	(0.141)	(0.146)
SIC38	0.270**	0.187	0.149
	(0.110)	(0.130)	(0.133)
SIC49	-0.451**	-0.568	-0.561
	(0.045)	(0.038)	(0.038)
Intercept	-0.243	-0.296	-0.118
	(0.071)	(0.123)	(0.588)
Log-Likelihood	-269.85	-199.76	-193.81
Chi-sq	91.36	231.55	243.44
(p-value)	(0.000)	(0.000)	(0.000)
N	459	459	459

Notes:

- Dependent Variable for this equation is EMS adoption variable (binary).

- We report marginal effects (except for intercept) here and standard errors are reported in parenthesis.

- *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.7: Determinants of Adoption of EMS System (with Proxy Vote Variable): Probit Models

Variable Name	Model I	Model II	Model III
PROXYVC	0.235***	0.291***	0.143
	(0.074)	(0.086)	(0.112)
NOEMPLOYEES89		0.001	0.002**
		(0.001)	(0.001)
FINALGOOD (Firm sells final product)		-0.215**	-0.038
		(0.098)	(0.113)
TOTALASSETS89		-0.006***	-0.010***
		(0.002)	(0.003)
SIERRA89		-0.041*	-0.018
		(0.024)	(0.026)
STRICT (State has strict liability statute)		-0.219**	-0.175*
		(0.088)	(0.102)
SPENDAIRQUA (State spending on air quality programs)		0.051	0.062
		(0.051)	(0.056)
EDUC		0.034**	0.025
		(0.018)	(0.020)
LAWYERSPERCAP		-0.213***	-0.141**
		(0.069)	(0.079)
RIGHTTOWORK (State has right to work statute)		-0.179**	-0.11
		(0.077)	(0.090)
SIERRA*FINALGOOD		-0.023	-0.045
		(0.037)	(0.040)
STRICT*NOEMPLOYEES		0.000	-0.001
		(0.001)	(0.001)
RELEMISSIONS89 (CAA emissions relative to industry)			0.030**
			(0.016)
CAAEMISSIONS89			0.076***
			(0.034)
EPAINSPECTIONS89			0.020***
			(0.006)
SIC28	0.514***	0.492***	0.504***
	(0.060)	(0.075)	(0.120)

Table 2.7: Determinants of Adoption of EMS System (with Proxy Vote Variable): Probit Models

Variable Name	**Model I**	**Model II**	**Model III**
SIC37	0.244**	0.103	0.009
	(0.099)	(0.116)	(0.143)
SIC38	0.249**	0.096	0.148
	(0.113)	(0.127)	(0.133)
SIC49	-0.458***	-0.480***	-0.564***
	(0.042)	(0.031)	(0.038)
Intercept	0.274	0.662	-0.133
	(0.072)	(0.530)	(0.588)
Log-Likelihood	-267.72	-238.27	-195.68
Chi-sq	95.32	154.52	239.7
(p-value)	(0.000)	(0.000)	(0.000)
N	459	459	459

Notes:

- Dependent Variable for this equation is EMS adoption variable (binary).
- We report marginal effects (except for intercept) here and standard errors are reported in parenthesis.
- *** significant at 1%, ** significant at 5%, * significant at 10%.

Table 2.8: Determinants of ISO 14001 Registration: Exponential Hazard Model

	Model I (1996-2003)	**Model II (1996-1999)**	**Model III (2000-2003)**
Variable Name	**Hazard Ratio (Std. Error)**	**Hazard Ratio (Std. Error)**	**Hazard Ratio (Std. Error)**
PROXYVOTE	1.937**	3.867***	1.341
	(0.650)	(1.857)	(0.682)
NOEMPLOYEES	1.002***	1.004***	1.002**
	(0.001)	(0.001)	(0.001)
FINALGOOD (Firm sells final	0.417***	0.181***	0.537*
product)	(0.120)	(0.109)	(0.188)
CAAEMISSIONS	0.819**	0.868	0.912
	(0.066)	(0.120)	(0.170)
RELEMISSIONS (CAA	1.009	1.018	0.798
emissions relative to industry)	(0.012)	(0.012)	(0.255)
EPAINSPECTIONS	1.018***	1.025***	1.014***
	(0.005)	(0.007)	(0.005)
TOTALASSETS	0.819	0.739	0.576*
	(0.132)	(0.166)	(0.168)
HERFINDEX (Herfindahl	3.125	8.301	1.685
index, 3 digit SIC)	(2.460)	(12.161)	(1.556)
RIGHTTOWORK (State has	0.423**	0.298	0.421*
right to work statute)	(0.180)	(0.243)	(0.211)
EDUC	1.183	0.854	1.307**
	(0.124)	(0.190)	(0.142)
LAWYERSPERCAP	0.628	1.503	0.402***
	(0.183)	(0.766)	(0.136)
AVERAGEINCOME	1.000	1.000	0.999
	(0.000)	(0.000)	(0.000)
SIERRA	0.917	1.337	0.913
	(0.181)	(0.662)	(0.166)
NREXPT (State spending	0.921	0.060**	0.998
on natural resources)	(0.296)	(0.078)	(0.287)
STRICT (State has strict	0.623	0.155**	1.058

Table 2.8: Determinants of ISO 14001 Registration: Exponential Hazard Model

	Model I (1996-2003)	**Model II (1996-1999)**	**Model III (2000-2003)**
Variable Name	**Hazard Ratio (Std. Error)**	**Hazard Ratio (Std. Error)**	**Hazard Ratio (Std. Error)**
liability statute)	(0.249)	(0.123)	(0.526)
SIC28	1.383	0.874	1.536
	(0.644)	(0.760)	(0.855)
SIC35	3.401***	1.876	4.154***
	(1.335)	(1.484)	(1.840)
SIC36	3.082***	3.483	3.224***
	(1.075)	(3.009)	(1.411)
SIC49	0.467	1.478	0.321
	(0.397)	(2.181)	(0.378)
SIC73	0.248	1.025	0.000***
	(0.258)	(1.178)	(0.000)
PERIOD [<2000]	0.006***		
	(0.008)		
PERIOD[>=2000]	0.011***		
	(0.015)		
Log Pseudolikelihood	-192.46	-62.97	-110.41
Chi-square	894.82	126.27	4983.26
(p-value)	(0.000)	(0.000)	(0.000)
N	2844	1272	1572

Notes:

- Dependent Variable for this equation is ISO 14001 registration variable (binary).
- Model I, II, and III are the same models which are estimated over different time periods.
- We report hazard ratios here and standard errors are reported in parenthesis.
- *** significant at 1%, ** significant at 5%, * significant at 10%.
- We included yearly dummies in all the models.We found yearly dummies to be jointly insignificant.
- We tested for equality of hazard functions (with respect to proxy vote variable).

We rejected the null of equality of hazard functions (p-value: 0.0584).

Table 2.9: Determinants of ISO 14001 Registration: Cox Proportional Hazard Model

	Model I (1996-2003)	**Model II (1996-1999)**	**Model III (2000-2003)**
Variable Name	**Hazard Ratio (Std. Error)**	**Hazard Ratio (Std. Error)**	**Hazard Ratio (Std. Error)**
PROXYVOTE	1.987*	4.015**	1.351
	(0.603)	(1.780)	(0.691)
NOEMPLOYEES	1.002***	1.004***	1.002**
	(0.001)	(0.001)	(0.001)
FINALGOOD	0.412***	0.178***	0.530*
(Firm sells final product)	(0.120)	(0.107)	(0.189)
CAAEMISSIONS	0.834***	0.884	0.914
	(0.065)	(0.098)	(0.167)
RELEMISSIONS	1.010	1.020	0.801
(CAA emissions relative to industry)	(0.014)	(0.012)	(0.245)
EPAINSPECTIONS	1.017***	1.023***	1.014***
	(0.005)	(0.007)	(0.006)
TOTALASSETS	0.818	0.736	0.567*
	(0.133)	(0.161)	(0.171)
HERFINDEX	2.985	7.797	1.651
(Herfindahl index, 3 digit SIC)	(2.408)	(11.151)	(1.542)
RIGHTTOWORK	0.411**	0.292	0.422*
(State has right to work statute)	(0.177)	(0.235)	(0.213)
EDUC	1.192*	0.882	1.303**
	(0.125)	(0.184)	(0.141)
LAWYERSPERCAP	0.622	1.448	0.402***
	(0.185)	(0.765)	(0.136)
AVERAGEINCOME	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)
SIERRA	0.898	1.177	0.923
	(0.178)	(0.638)	(0.167)

Table 2.9: Determinants of ISO 14001 Registration: Cox Proportional Hazard Model

	Model I (1996-2003)	**Model II (1996-1999)**	**Model III (2000-2003)**
Variable Name	**Hazard Ratio (Std. Error)**	**Hazard Ratio (Std. Error)**	**Hazard Ratio (Std. Error)**
NREXPT	0.931	0.070*	0.975
State spending on natural resources)	(0.297)	(0.097)	(0.272)
STRICT	0.611	0.151**	1.062
(State has strict liability statute)	(0.250)	(0.116)	(0.531)
SIC28	1.355	0.850	1.544
	(0.641)	(0.743)	(0.859)
SIC35	3.410***	1.855	4.173***
	(1.356)	(1.443)	(1.858)
SIC36	3.121***	3.587	4.252***
	(1.100)	(3.067)	(1.423)
SIC49	0.455	1.413	0.324
	(0.385)	(2.101)	(0.383)
SIC73	0.246	1.013	0.000***
	(0.257)	(1.168)	(0.000)
Log Pseudolikelihood	-374.44	-90.65	-266.63
Chi-square	88.60	118.78	19762.08
(p-value)	(0.000)	(0.000)	(0.000)
	26.77	23.23	19.04
Test: Proportional Hazards			
(p-value)	0.14	0.28	0.52
N	2844	1272	1572

Notes:

- Dependent Variable for this equation is ISO 14001 registration variable (binary).
- Model I, II, and III are the same models which are estimated over different time periods.
- We report hazard ratios here and standard errors are reported in parenthesis.
- *** significant at 1%, ** significant at 5%, * significant at 10%.
- We conducted the test of proportional hazards. Chi-sq(20) fails to reject the null of proportional hazards.

Table 2.10: Estimation Results for Pollution Equation

Variable	Random Effects Model Estimate	Random Effects Model Std. Err.	Fixed Effects Model Estimate	Fixed Effects Model Std. Err.
LAG2PROXYVOTE	-0.128**	0.059	-0.102*	0.055
NOEMPLOYEES	0.004***	0.001	0.001	0.002
EMPLYSQ	-0.133	0.132	0.081	0.157
EPAINSPECTIONS	0.004	0.003	0.002	0.002
SALESGROWTH	-0.003	0.012	0.000	0.011
HERFINDEX (Herfindahl index, 3 digit SIC)	0.183	0.376	-0.597	0.428
FINALGOOD (Firm sells final product)	-0.163*	0.096	0.049	0.099
NREXPT (State spending on natural resources)	-0.04	0.119	0.158	0.176
AVERAGEINCOME	83.095**	36.320	143.27***	48.447
SIERRA	-3.001	2.259	-2.799	2.075
STRICT (State has strict liability statute)	-0.293***	0.106	-0.391***	0.114
EDUC	0.032	0.042		
RIGHTTOWORK (State has right to work statute)	-0.368	0.252		
LAWYERSPERCAP	-0.472**	0.187		
SIC28	0.114	0.391		
SIC35	0.616	0.440		
SIC36	-0.501	0.387		
SIC37	0.978**	0.494		
SIC38	-0.567	0.492		
SIC49	-0.758**	0.382		
SIC60	-0.876**	0.408		
SIC63	-0.765*	0.449		
SIC73	-0.765*	0.402		
Intercept	0.812	0.823	1.217	0.226
Time Effects	YES		YES	
LM Test: OLS vs. RE (p-value)	12557.86 (0.000)			
F Test: OLS vs. FE (p-value)			1.250 (0.000)	
Hausman Test: RE vs. FE	159.36			

Table 2.10: Estimation Results for Pollution Equation

Variable	**Random Effects Model**		**Fixed Effects Model**	
	Estimate	**Std. Err.**	**Estimate**	**Std. Err.**
(p-value)	(0.000)			

Notes:

- Dependent variable for this equation is toxicity weighted emissions. This table reports results from estimations where disturbance term is assumed to be first order autoregressive.
- We have conducted Breusch-Pagan LM test to test OLS vs. RE. We reject the null in favor of random effects.
- F-test of OLS vs. FE provides evidence in favor of fixed effects.
- Hausman test is utilized to test RE vs. FE. We find evidence in favor of fixed effects.
- LM test is conducted without assuming autoregressive errors.
- *** significant at 1%, ** significant at 5%, * significant at 10%.

Chapter 3

The Great Depression, the National Recovery Administration, Technological Innovation and Total Factor Productivity: 1919-1939

3.1 Introduction

The first half of the twentieth century witnessed significant growth in total factor productivity (TFP).[1] Scholars who examine productivity changes in the 1930s have relied heavily on Kendrick's (1961) estimates of productivity for national aggregates.[2] Despite the common sources for TFP estimates, they tell quite different stories about productivity change during the 1930s. Ohanian (2001) emphasizes the dramatic drop in TFP during the early Depression years both in absolute and relative terms. Ohanian (2001) argues that in the "average" post-war recession TFP declines by 0.3 percent and output declines by 2 percent, a ratio of TFP decline to output decline of 0.15. Between 1929 and 1933, real output declined by 29 percent. Based on the typical recessionary ratio of TFP decline to output decline, TFP would have declined by roughly 4 to 5 percent. The actual TFP decline was much more dramatic at 18 percent. Cole & Ohanian (1999) observe that TFP quickly returned to trend by 1936 and continued along the long-term trend after 1936.

Field (2003) and Field (2005), on the other hand, refer to the years 1929-1941 as the *most technologically progressive* years of the century. Overall TFP growth

[1] TFP is measured as the difference between real output and a weighted average of inputs. Abramovitz (1956) and Solow (1957) refer to total factor productivity as "residual". This residual is measured as gap between the growth rate of real GDP and a weighted average of labor and capital inputs. The weights are the corresponding shares of these factors in national income Field (2005). Abramovitz (1956) concluded than an increase in this "residual" reflected a shift to a knowledge-based type of economic development.

[2] See Cole & Ohanian (1999) and Ohanian (2001).

between 1929 and 1941 was the highest of any comparable period in the twentieth century. Labor and capital inputs were at the same level in 1941 as they were in 1929. However, real output experienced an increase of 32.3 percent. All this growth in output and output per hour occurred due to TFP growth, which Field attributes to several advancements in processes, product breakthroughs, and advances in transportation and public utilities and distribution particularly in electricity generation.

My goal is to shed new light on productivity change during the 1920s and the Great Depression following a two-stage process. In the first stage, I develop new estimates of total factor productivity for eight industries using a cost-function approach with panel data for each industry disaggregated to the state level for every odd year between 1919 and 1939. At the very least the new estimates provide a check of the robustness of Kendrick's (1961) estimates using national aggregates. The new estimates also provide new opportunities for exploring productivity change that are not available from Kendrick's (1961) estimates. In the second stage, I use a combination of quantitative and narrative evidence to examine the factors that influenced changes in TFP across states and time during the 1920s. The focus in this version of the paper is on the motor vehicle and parts and cotton goods industry. As I move forward, I will also explore the lumber and timber products, printing and publishing, boots and shoes, bread-making, iron and steel, and meatpacking industries.

My TFP estimates show that each industry followed a different path of TFP change. The motor vehicles industry experienced declining TFP throughout the time period 1919-39, and had not yet returned to its peak level by 1939. Meanwhile, boots and shoes, bread manufacturing, cotton goods, and printing and publishing experienced an increase in TFP over the entire time period. The iron and steel industry TFP fluctuated greatly throughout the 1920s and 1930s. TFP in 1923 sunk 96 percent below its 1919 level, started recovering from 1925 and showed recovery until 1929. Iron and steel manufacturing TFP peaked again in 1933 before falling dramatically from 1933 through 1939. In contrast, to the economy wide descriptions by Cole & Ohanian (1999), I do not find consistent evidence of a large TFP decline during the years 1929-33 in the industries studied. I do not find that 1930s were the period of interrupted TFP growth but I do find that five industries out of eight had higher productivity in the 1930s than in the 1920s. Overall, our analysis provides some evidence in favor of Field (2003) and Field (2005) rather than Ohanian (2001) and Cole & Ohanian (1999).

The second stage of the analysis focuses on the impact of the National Recovery Administration (NRA) and other factors on TFP in the motor vehicles and cotton goods industry. The Roosevelt administration established the National Recovery Administration (NRA) in 1933 for two loosely related purposes. They wished to - halt an epidemic of business failures, and improve conditions for workers by simultaneously raising prices and wages, while limiting working hours in an attempt to increase the number of workers employed (Alexander 1997). The NRA designated code authorities were formed from trade associations and other industry groups and established "codes of fair competition" that were approved if the industry raised wages and accepted collective bargaining with an independent union. In return, the act suspended antitrust law and each industry was encouraged to adopt practices that led to limited competition and higher prices. By May 1935, when the NIRA was struck down by the Supreme Court, almost 800 codes had been implemented, covering the vast majority of non-farm workers. It is suspected by some economists that President Roosevelt's "New Deal" cartelization policies, which limited competition in product markets and increased labor bargaining power, kept the economy depressed after 1933 and did not let it recover to its pre-Depression era levels.

Second stage analysis for the motor vehicles and cotton goods industry shows that TFP fell with increases in employment and strike activity. However, capacity utilization was positively related with TFP for the motor vehicles industry but had a negative relationship with TFP for cotton goods industry. The NRA code might have contributed to a decline in TFP as it led to incentives to raise employment, strikes, and reduce capacity utilization. However, year fixed effects for 1933 and 1935 suggest that additional effects of the NRA were positive for both the industries.

3.2 Literature Review

In recent years, the productivity pattern during the Depression years has attracted attention from many economists as it is believed that identifying the causes of changes in productivity can help understand the Great Depression better.Ohanian (2001) observes that between 1929 and 1933, real output per adult fell over 30 percent, and total factor productivity (TFP) fell about 18 percent. This TFP decrease is much larger than the usual TFP decrease (about 4-5 percent) that occurs during postwar recessions. It is hard to explain this decline in terms of "technological regress". He analyzes productivity data using Kendrick's (1961) data and suggests four explanations for the Great Depression: changes in the capacity utilization, changes in the composition of production, labor-hoarding, and increasing returns. Ohanian (2001) also explores sectoral data due to the inability of factor mis-measurements to explain the aggregate TFP decline. Table 3.1 shows productivity in 1933 relative to 1929 in each sector and also shows sector employment in 1933 as a percentage of its 1929 level. It is clear from the Table 3.1 that aggregate productivity fell much more than sectoral productivity. Manufacturing and railroads are the only sectors that show substantial declines in TFP. He considers labor hoarding and increasing returns to scale as possible explanations for this sectoral TFP decline but does not find them to be major contributors to TFP decline. He suggests two other explanations: measurement error and lower production efficiency.

Cole & Ohanian (1999) examine both the decline in economic activity from 1929-33 and the weak recovery between 1934-39. Table 3.2 shows that after including 1939 in the analysis, both labor productivity and total factor productivity fell sharply through 1933 then recovered to slightly above their 1929 levels by 1939. This pattern in TFP raises the question - Why did consumption and investment remain so low in a period characterized by rapid productivity growth? Cole & Ohanian (1999) suggest that this puzzle can be answered by looking for shocks with special characteristics; for instance, a shock that does not hit all sectors of the economy proportionately. To explore this possibility, Cole & Ohanian (2005) assess the role of deflation/monetary shocks and productivity shocks as the major contributors to the Great Depression. They find that the productivity shocks explain about two-thirds of the declines associated with the Great Depression. They also find some evidence that these shocks were largely related to industrial activity rather than agricultural activity.

In contrast, Field (2003) and Field (2005) argue that the years 1929-1941 were the most technologically progressive years in U.S. economic history. In part this arises from using TFP measures from the peace economy of 1947 as the measure of TFP for the year 1941. Field argues that the command economy during World War II was so focused on the war that there were few advances in the production of normal peacetime goods and services. Table 3.3 presents compounded annual average growth rates of MFP and shows that the years 1929-41 attained the highest MFP productivity growth rates between 1919 and 1948. Field (2003) advocates that the advances made in techniques during the Depression years laid the foundation for the labor and Multi Factor Productivity (MFP) growth in 1950's and 1960's. However, the depression years were very different from the years 1919-29 both in terms of aggregate TFP growth and its sources (Field 2005). TFP growth in the 1920s primarily came from the manufacturing sector. The share of TFP growth accounted for by manufacturing fell from 83 percent in the 1920s to 48 percent between 1929 and 1941. Also, in contrast to the 1920s, the TFP growth in later years took place in the absence of any net capital accumulation. During the Depression years, industries like transport equipment and primary metal industries experienced negative productivity growth, but there were also a large number of dynamic sectors. Several manufacturing industries like textiles, paper, rubber, chemicals, leather, petroleum and coal products along with communications services, electric utilities, transportation and railroads progressed in the 1930s.

Usually technical advances do not come in a steady stream, but the 1930s were exceptional in the sense that there were advances in a large number of industries. Some advances worth mentioning are: technical advancements in chemistry that lengthened the life of structures or equipment; a trend towards larger units in the case of equipment and fixed installations, and advances in thermal efficiency, particularly in the electric power generating industry. Field (2005) points to the fact that output of electricity in 1941 was 86.5 percent above its 1929 level.

Devine (1983) and David & Wright (2003) focus on the rapid growth in the electric power generating industry following World War I. Devine (1983) claims that during the late 1910s and 1920s, the electric unit drive became the most common way of driving machinery and the electric utility became the primary provider of power for the manufacturing sector. David & Wright (2003) propose that supply-side changes, like allowing the utilities to escape regulation by municipal and town governments, propelled electricity as a main power source in US manufacturing. Electrification led to a significant decline in the capital-output ratio during the 1920s. Electrification was particularly instrumental in reducing the fixed capital needed by a plant by eliminating heavy shafts and belting. This change allowed the factories to be more lightly constructed and also led to a reduction in the frequency of downtime. Entire plants were no longer shut down to make changes in one department. Electrification also may have exerted a positive influence on the efficiency of labor channels by increasing the utilization of labor capacity and demand for reliable employees and by increasing the scope for individual specialization. Both studies point to the important role electricity could play in TFP growth. I am in the process of including electricity usage in the analysis.

The conflicting interpretations of TFP change during the Great Depression, and the large variation in TFP experience in different manufacturing industries suggest that it would be useful to re-estimate total factor productivity at a more disaggregate level during the 1920s and 1930s. At the very least, the new estimates will provide a robustness check for Kendrick's (1961) estimates. More importantly, by developing state level estimates of total factor productivity, I can also perform hypotheses tests about the various factors that might have influenced TFP change.

In addition to the various influences of capacity utilization and technological change described above, I plan to examine the impact of the National Recovery Administration and the President's Reemployment Agreement (PRA). Several economists suggest that that the National Recovery Administration (NRA) established in 1933 by President Franklin Roosevelt was a key contributor to the slow recovery from the Depression because the NRA limited competition in the product market and increased labor bargaining power ((Alexander 1997), (Alexander 1994), (Cole & Ohanian 2004), and (Taylor 2008)). Cole & Ohanian (2004) argue that the NRA, limited antitrust enforcement, and the National Labor Relations Board's strengthening of bargaining power for labor unions account for more than half of the slow recovery from 1933 through 1939. Alexander (1994) conducted cross-sectional analysis of Census of Manufactures data and established that on balance, the NRA facilitated collusion in unconcentrated industries. Alexander (1997) examined the macaroni industry and found that industries characterized by homogenous cost structures had relatively better chance of successful cooperation under the NRA. Taylor (2008) analyzes a panel of 66 industries to identify specific attributes of NRA codes that facilitated collusion. He finds that output was lower in this time period, consistent with the cartel theory and that industries with more complex codes were more successful than the ones with simpler codes. Although productivity changes influence the analysis of the NRA, as yet, there have been no direct studies of the impact of the NRA and National Labor Relations Board (NLRB) on TFP.

3.2.1 Kendrick's Methodology

Most of the literature that focuses on productivity changes during the depression era particularly - work by Ohanian (2001), Cole & Ohanian (1999), Field (2003), and Field (2005), has used Kendrick's estimates for their analysis. Given the importance of the productivity measures developed by Kendrick (1961), I discuss here the data sources and methodology he employed to calculate these productivity measures. Kendrick (1961) worked in terms of productivity ratios rather than fitting regression equations to output and input data. His rationale for using productivity ratios was that they provide greater flexibility for the analysis of movements and of relationships with other variables. He developed both total factor productivity and partial productivity ratios. The Total Factor Productivity ratio relates the real product to total factor inputs. Partial productivity ratios are ratios of output to particular inputs, for example output per man-hour or output per unit of capital unit.

In order to construct Total Factor Productivity, as defined by Kendrick, information on the physical volume of output, labor input and capital input is required.

Data on the physical volume of output was provided by Solomon Fabricant's production indexes over the time period 1899-1939. Fabricant computed an "unadjusted" production index by multiplying the number of units of each type of commodity by the average unit value for the two years being compared.[3] He adjusted this index for changes in coverage or incomplete coverage to arrive at the more reasonable production index.[4] He used 40 percent as the cut off to construct the industry output index. In other words, only if the value of the covered products primary to an industry were 40 percent or more of the total value of industry output in most census years, did he then construct an output index. The construction of these production indexes required assumptions regarding what products are primary to a particular industry, how to deal with overlapping of products across industries, and how to handle changes in the definition of a particular industry overtime.

Calculation of Total Factor Productivity requires combining weighted shares of two major classes of factor inputs, labor (measured by man-hours) and capital to arrive at total factor input for major industry groups. Man-hours are weighted by the base-period average hourly labor compensation and the real capital stock is weighted by the base-period rate of return on capital.[5] An index of total man-hours worked in the various industries is obtained by multiplying indexes of total employment by indexes of average hours worked by production workers. Employment estimates for industries and groups are based on data from the *Census of Manufactures.* The employment indexes are based on the sum of persons engaged in the several classes of

[3]Fabricant used Marshall-Edgeworth formula given by: $\sum q_1(p_0 + p_1)/\sum q_0(p_0 + p_1)$, where q represents number of units of output, p their average prices; and the subscripts 0 and 1, the base period and the given period respectively. Fabricant used 1919 to compare 1909 and 1914; and 1929 as base to compare other census years through 1939.

[4]See Appendix A in *The Output of Manufacturing Industries in the United States, 1899-1937* by Solomon Fabricant and Appendix D in *Productivity Trends in the United States* by John Kendrick for details on coverage adjustment.

[5]See Technical Note to Appendix D in *Productivity Trends in the United States* by John Kendrick for details on weights for different industries.

work distinguished by the Census: wage earners, salaried employees, and proprietors and firm members.

The data on actual hours worked is relatively harder to come by and involved a significant amount of interpolation and extrapolation. In order to calculate average work hours in 1930s based on 1947 data, the BLS estimates of average hours worked per week were used as the main means of extrapolation. In the case of industries that were not covered by the BLS, an estimate of average actual hours was obtained by using special Census tabulations based on large-industry samples of average hours worked per week. A few industries also suffered from lack of data for 1937. In that case interpolation was used to obtain a measure of hours worked. Due to lack of a consistent source of data, it was even more difficult to construct a measure of hours worked for the years 1929 and earlier. Kendrick (1961) has relied on estimates of standard hours worked per week, adjusted to approximate actual hours. He computed averages for each industry, group, and segment by using frequency distributions of wage earners by standard-hours classes for all manufacturing industries. These frequency distributions were presented in the Censuses of 1909, 1914, 1919, 1921, 1923, and 1929. In all the cases, the midpoints of the hour classes were used. All the hours estimates were adjusted on the basis of the ratio of the BLS actual hours for all manufacturing to the standard hours estimates. Hence, in order to generate a complete average hours worked series, required pooling data from several sources and making several adjustments in order to arrive at a reasonable measure. Finally, the index of total man-hours worked was obtained by multiplying the index of average hours worked by production workers by indexes of total employment. This procedure requires the strong assumption that average hours worked by nonproduction workers have moved with those worked by production workers.

The estimates of real capital stock in manufacturing used by Kendrick are based mainly on the estimates underlying Creamer's *Capital and Input Trends in Manufacturing Industries*. Creamer's estimates for 1919 and prior years are derived from data on the net book value of capital given in the *Census of Manufactures*. The Census stopped collecting this data from 1921 onwards due to unreliability of this data. It is not clear what this data represents and if it is a good measure of capital in 1919 and prior years. The capital estimates for 1929 through 1953 are based on data for corporations, obtained from the Internal Revenue Service. He adjusted this data for industrial comparability, noncorporate establishments, and for price changes. Kendrick adjusted these estimates to eliminate financial capital items and to attain better industrial comparability. This adjustment for 1929 to 1953 is simple due to easy availability of data on inventories from Internal Revenue tabulations. However, an estimate of inventories for 1919 and prior years required collection of data from several sources and interpolation. This section emphasizes that any method that is employed to estimate TFP would require several strong assumptions. In Kendrick's case those assumptions were mostly related to data construction and in our case they are mostly related to estimation procedure.

3.3 Methodology

3.3.1 Empirical Model

Most of the literature related to productivity changes during the depression era has used Kendrick's (1961) productivity measures with some adjustments. I follow an alternative strategy of estimating the parameters of the production function using a cost function approach. This approach allows me to construct TFP measures for every odd year between 1919 and 1939, whereas Kendrick could only construct TFP measures for a few selected years: 1899, 1909, 1919, 1929, 1937, 1948, 1953 and 1957. These TFP measures are very useful in understanding the long term trends in TFP but not very informative about the period 1919-1939 and movements in TFP over this time period.

The advantages of using a cost function approach rather than production function are well documented in the literature. The cost function approach allows us to avoid problems with endogenous input quantities. The cost function uses market prices of inputs, which are more likely to be determined exogenously to the firm, than the factor quantities used in the production function approach (Binswanger 1974).

A number of scholars have used the cost function approach. Binswanger (1974) outlines the approach to using the Translog cost function along with the share equations to estimate a system of equations. This strategy can also be used to account for neutral and non-neutral efficiency differences. Ray (1982) has used a Translog cost function approach to analyze US agricultural production in a multi output context. The Translog cost function approach has also been employed by Christensen & Greene (1976) to estimate economies of scale for US firms producing electric power. They answer the question of whether increased competition in the electric industry at the generation phase would sacrifice economies of scale. They make the crucial assumption that output for electric power is exogenous. Electric utilities are required to supply all the electric power demanded at the regulated prices. However, this is not a reasonable assumption as output can fluctuate due to demand fluctuations or other reasons. This shortcoming can be overcome by instrumenting for the output.

Baltagi & Griffin (1988) specify the underlying cost function as Translog to develop a general index of technical change and TFP. Given the structure of my data, I have opted for the cost function approach rather than production function[6] or index

[6] Several specifications of production functions are utilized to estimate TFP. The simplest formulation is: $y_{it} = f_{it}(k, x) + e_{it}$;$e_{it} = \omega_{it} + \mu_{it}$. Here, y_{it} is gross output, $f(.)$ is any production

number approach.[7] I have specified that cost takes the Translog functional form. The Translog functional form has been used extensively in the literature. The functional form is flexible enough that it places no artificial restrictions on the elasticity of substitution. The Translog also allows the flexibility to take into account neutral or non-neutral efficiency and also neutral and non-neutral economies of scale. As the Translog nests other functional forms, it is possible to test the restrictions on the other functional forms and choose the model that fits the data best.

Baltagi & Griffin (1988) methods for estimating Total Factor Productivity (TFP) allow me to estimate both TFP at a point in time and changes in TFP over time.

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technology, x_{it} is a vector of all factors of production other than capital, k_{it} is capital. ω_{it} is plant level efficiency observed by the plant but not by the econometrician. μ_{it} is an unexpected productivity shock unobserved by the plant and the econometrician. A plant's knowledge of it affects its choice of inputs. The fact than an econometrician cannot observe ω_{it} generates a bias in the estimation. This results in biased estimates of parameters if the production function is estimated using Ordinary Least Squares (OLS). Some studies have dealt with this problem by specifying ω_{it} as ω_i, that is productivity is plant specific but time invariant. This model is estimated using fixed effects estimation. However, the assumption of time invariant productivity is not reasonable at the time of a large structural change like an economic depression. This also does not let us observe how productivity evolves over time due to changes in the production structure. This drawback can be overcome by specifying plant specific and time varying productivity as a function of time. This procedure requires a parametric specification of the productivity which might not be desirable in all the situations. This strategy has been followed by Christopher Cornwell (1990), Liu (1993) and Liu & Tybout (1996). This procedure requires estimation of the production function using a fixed effects model. The parameter estimates from this regression is used to construct a measure of productivity. Even if the parametric specification of productivity is not a problem, the use of fixed effects still generates biased estimates. One could overcome this shortcoming by using the GMM estimator proposed by Blundell & Bond (1998). This methodology is usually not appropriate in the case where one faces the problem of selection bias due to plant exit. Olley & Pakes (1996) and Pavcnik (2002) estimate the production function semi-parametrically to deal with the problem of plant exit and simultaneity bias. They use these estimates to develop measures of plant-level productivity. We need not worry about plant exit as we have industry level data and no plant specific information. We still need to explore how we can alter this estimation procedure to fit the situation where we have a cost function to estimate and we have aggregate level data instead of plant level data.

[7]Keay (2000) and Inwood & Keay (2005) use a Tornqvist index number approach to derive TFP ratios. I can use either the production function approach or the cost function approach to derive these index numbers. However, in our case the cost function approach requires information on the price of output for all the years and the production function approach requires information on physical units of gross output, labor, capital and materials. We do not have information on price of output, physical units of gross output, labor, and materials. Hence, TFP is estimated by econometric estimation of the cost function.

I consider the costs to be a function of output[8], and four input prices: the average wage rate, the average salary rate, the price of materials, and the price of capital. For the moment a time trend is employed as a proxy for technical change. The time trend representation of technical change is non-neutral and scale augmenting if the Translog cost function takes the form given below. The Translog cost function is a second order logarithmic Taylor series approximation of an analytic cost function. It takes the following form, after identifying derivatives as coefficients and assuming equality of cross-product derivatives:

$$\begin{aligned} \ln C^* = \alpha_0 + \sum_{i=1}^{4} \alpha_i \ln P_i + \sum_{r=1}^{2} \delta_r \ln Z_r + \frac{1}{2} \sum_{i=1}^{4} \sum_{j=1}^{4} \alpha_{ij} \ln P_i \ln P_j \\ + \frac{1}{2} \sum_{r=1}^{2} \sum_{n=1}^{2} \delta_{rn} \ln Z_r \ln Z_n + \sum_{i=1}^{4} \sum_{r=1}^{2} \tau_{ir} \ln P_i \ln Z_r + \epsilon \end{aligned} \tag{3.1}$$

where,

C^* is profit maximizing total cost

$P_{i,j}$ $i, j = 1...4$ prices (average wages, average salaries, material price, interest rate)

$Z_{r,n}$ $r, n = 1...2$ (output, time trend)

ϵ remainder of the Taylor series

Symmetry in the interaction between variables requires that $\alpha_{ij} = \alpha_{ji}$ and $\delta_{rn} = \delta_{nr}$. A cost function must be homogenous of degree one to correspond to a well-behaved production function. Homogeneity imposes the following restrictions on the

[8]Due to lack of data on output, value added is used as a proxy for output. Several studies use value added as a proxy for output (see Basu, Fernald & Kimball (2006), Chang & Hong (2006), and Unni, Lalitha & Rani (2001)). Inwood & Keay (2005) employ total value of production to estimate TFP. However, their qualitative conclusions are not affected by the use of value added or gross output.

parameters:

$$\sum_{i=1}^{4} \alpha_i = 0 \tag{3.2}$$

$$\sum_{i=1}^{4} \alpha_{ij} = \sum_{j=1}^{4} \alpha_{ji} = \sum_{i=1}^{4}\sum_{j=1}^{4} \alpha_{ij} = 0 \tag{3.3}$$

$$\sum_{i=1}^{4} \tau_{ir} = 0 \tag{3.4}$$

The Translog cost function can be estimated as a single equation or as a system of share equations with or without the cost function. The share equations (or derived demand function) can be easily computed by differentiating the cost function with respect to the factor prices:

$$s_i = \frac{\partial \ln C^*}{\partial \ln P_i} = \alpha_i + \sum_{j=1}^{4} \alpha_{ij} \ln P_j + \sum_{r=1}^{2} \tau_{ir} \ln Z_r \tag{3.5}$$

I get the result $\frac{\partial \ln C^*}{\partial \ln P_i} = \frac{X^* P_i}{C^*} = s_i$, after applying Shepherd's Lemma that says $\frac{\partial \ln C^*}{\partial \ln P_i} = X^*$ and the result that $\frac{\partial \ln C^*}{\partial \ln P_i} = \frac{C^*}{\partial P_i} . \frac{P_i}{C^*}$. Here, s_i is factor $i's$ share of total cost. We get following equations:

$$\begin{aligned}
S_w = S_1 &= \alpha_1 + \alpha_{11} \ln P_1 + \alpha_{12} \ln P_2 + \alpha_{13} \ln P_3 + \alpha_{14} \ln P_4 + \tau_{11} \ln Y + \tau_{12} \ln T \\
S_k = S_2 &= \alpha_2 + \alpha_{21} \ln P_1 + \alpha_{22} \ln P_2 + \alpha_{23} \ln P_3 + \alpha_{24} \ln P_3 + \tau_{21} \ln Y + \tau_{22} \ln T \\
S_s = S_3 &= \alpha_3 + \alpha_{31} \ln P_1 + \alpha_{32} \ln P_2 + \alpha_{33} \ln P_3 + \alpha_{34} \ln P_4 + \tau_{31} \ln Y + \tau_{32} \ln T \\
S_m = S_4 &= \alpha_4 + \alpha_{41} \ln P_1 + \alpha_{42} \ln P_2 + \alpha_{43} \ln P_3 + \alpha_{44} \ln P_4 + \tau_{41} \ln Y + \tau_{42} \ln T
\end{aligned} \tag{3.6}$$

where,

$S_w = S_1 =$ Wage share of total cost; $S_s = S_2 =$ Salary share of total cost;

$S_k = S_3 =$ Capital share of total cost; $S_m = S_4 =$ Materials share of total cost;

$P_1 =$ Average wage rate; $P_2 =$Interest Rate;

$P_3 =$ Average Salary Rate; $P_4 =$ Price of materials;

$Y =$ Output; $T =$ Time trend

The condition $\alpha_{ij} = \alpha_{ji}$ results in the following cross equation restrictions. These restrictions follow from the Young's Theorem and imply that the coefficient on j^{th} and k^{th} price is same in the k^{th} and j^{th} equations respectively. For instance, the coefficient on the wage in the salaried labor share equation is same as the coefficient on salary in the wage labor share equation.

$$\alpha_{14} = \alpha_{41}; \alpha_{13} = \alpha_{31}; \alpha_{34} = \alpha_{43} \tag{3.7}$$

$$\alpha_{12} = \alpha_{21}; \alpha_{23} = \alpha_{32}; \alpha_{24} = \alpha_{42} \tag{3.8}$$

Equation 3.9 is same as equation 3.1. Using Shepherd's Lemma cost shares are given by as earlier in equation 3.5. Replacing Zs with T and Y in equation 3.1, I get the equation 3.9. After estimating equation 3.9 and deriving cost shares from this equation, the rate of technical change is given by equation 3.10.

$$\begin{aligned} \ln C^* = \alpha_0 + \sum_{i=1}^{4} \alpha_i \ln P_i + \gamma \ln Y + \delta \ln T + \frac{1}{2} \sum_{i=1}^{4} \sum_{j=1}^{4} \alpha_{ij} \ln P_i \ln P_j \\ + \frac{1}{2} \gamma^* (\ln Y)^2 + \frac{1}{2} \delta^* (\ln T)^2 + \sum_{i=1}^{4} \phi_i \ln T \ln P_i + \sum_{i=1}^{4} \psi_i \ln Y_i \ln P_i + \theta \ln T \ln Y \end{aligned} \tag{3.9}$$

where,

C^* is profit maximizing total cost

$P_{i,j}$ $i, j = 1...4$ prices (average wages, average salaries, material price, interest rate)

Y is output

T is a simple time trend

$$\dot{T} = \frac{\partial \ln C^*}{\partial T} = \delta + \delta^* T + \sum_{i=1}^{4} \phi_i \ln P_i + \theta \ln Y \tag{3.10}$$

The growth in technical change can be decomposed in the three components: (1) effect due to pure technical change: $\delta + \delta^* T$, (2) effect due to non-neutral technical change: $\sum_{i=1}^{4} \phi_i \ln P_i$ and (3) effect due to scale augmenting technical change: $\theta \ln Y$.

Using the estimates of technical change from equation 3.10, I can compute the estimated percentage change in total factor productivity $\widehat{T\dot{F}P}$ as:

$$\widehat{T\dot{F}P} = -\dot{T} + (1 - \epsilon_{CY})\dot{Y} \tag{3.11}$$

where, ϵ_{CY} is the elasticity of cost with respect to output.

$\widehat{T\dot{F}P}$ and observed change in TFP will differ from each other due to the restrictive characterization of technical change in equation 3.9. It is possible to define an improved measure of technical change that is more general than the earlier measure. In this general index of technical change, T and T^2 are replaced by a purely general index of technical change $A(t)$ as follows:

$$\begin{aligned} \ln C^* = \alpha_0 + A(t) + \sum_{i=1}^{4} \alpha_i \ln P_i + \gamma \ln Y + \frac{1}{2} \sum_{i=1}^{4} \sum_{j=1}^{4} \alpha_{ij} \ln P_i \ln P_j \\ + \frac{1}{2} \gamma^* (\ln Y)^2 + \sum_{i=1}^{4} \phi_i A(t) \ln P_i + \sum_{i=1}^{4} \psi_i \ln Y_i \ln P_i + \theta A(t) \ln Y \end{aligned} \tag{3.12}$$

The corresponding cost shares are:

$$S_i = \alpha_i + \sum_{j=1}^{4} \alpha_{ij} \ln P_j + \phi_i A(t) + \psi_i \ln Y_i \tag{3.13}$$

It is not possible to estimate equations 3.12 and 3.13 as $A(t)$ is not observable. However, it is possible to estimate equations 3.12 and 3.13 by using time dummies. I have data for eleven years; hence the equation will include time dummies for eleven years.

$$\begin{aligned}\ln C^* = \sum_{t=1}^{11} \eta_t D_t + \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4} \alpha_{ij} \ln P_i \ln P_j + \frac{1}{2}\gamma^* (\ln Y)^2 \\ \sum_{i=1}^{4}\sum_{t=1}^{11} \alpha_{it}^* \ln P_i D_t + \sum_{i=1}^{4} \psi_i \ln P_i \ln Y_i + \sum_{t=1}^{11} \theta_t^* D_t \ln Y\end{aligned} \tag{3.14}$$

where,D_t is a time specific dummy. The corresponding share equation is:

$$S_i = \sum_{t=1}^{11} \alpha_{it}^* D_t + \sum_{j=1}^{4} \alpha_{ij} \ln P_j + \psi_i \ln Y_i \tag{3.15}$$

Equations 3.14 and 3.15 are the same as equations 3.12 and 3.13 if and only if the following conditions are satisfied:

$$\eta_t = \alpha_0 + A(t) \tag{3.16}$$

$$\alpha_{it}^* = \alpha_i + \phi_i A(t) \tag{3.17}$$

$$\theta_t^* = \gamma + \theta A(t) \tag{3.18}$$

I can get the estimates for $A(t)$ by imposing the restrictions in equations 3.16 to 18 on the system of equations given by 3.14 and 3.15. I take the initial year as the base year and set $A(1) = 0$. This allows me to identify all other parameters. This model also allows me to calculate the rate of technical change comparable to the one given by equation 3.10:

$$\dot{T} = A(t) - A(t-1) + \sum_{i=1}^{4} [A(t) - A(t-1)] \ln P_i + \theta [A(t) - A(t-1)] \ln Y \tag{3.19}$$

As in the case of earlier index, I can decompose the technical change into the following three components: (1) the effect of pure technical change: $A(t) - A(t-1)$;

(2) the effect of non-neutral technical change: $\sum_{i=1}^{4}[A(t)-A(t-1)]\ln P_i$; and (3) the effect of scale augmentation: $\theta[A(t)-A(t-1)]\ln Y$. So far, I have used a simple index of technical change to construct a measure of productivity. I am currently working on using a general index of technical change to estimate TFP.

After estimation of industry level TFP, I specify a regression equation to identify the main factors that can explain changes in TFP overtime. Since I estimated TFP for each industry separately, I intend to specify a different equation for each industry. I have conducted preliminary analysis of the motor vehicles and cotton goods industry. The equation estimated is given by:

$$\begin{aligned} TFP_{s,t} = \beta_0 + \beta_1 STRIKE_{s,t} + \beta_2 CAPACITY_t + \beta_3 OUTPUT\_CHANGE_{s,t} + \\ \beta_4 EMPLOYMENT_{s,t} + \beta_5 Z_t + \Sigma_{j=6}^{15}\beta_j YEAR + \epsilon_{s,t} \end{aligned} \tag{3.20}$$

where, $TFP_{s,t}$ is the un-weighted measure of TFP in state s in year t in the industry (cotton goods or motor vehicles). **YEAR** is a vector of year indicators, **STRIKES** is the number of strikes in state s in year t, **CAPACITY** measures the capacity utilization in the motor vehicles industry[9], **OUTPUT_CHANGE** measures the change in output as compared to the last year in state s in year t, **EMPLOYMENT** measures the number of workers employed in state s in year t and **Z** accounts for any other industry specific changes, for example technological changes or changes in the industry due to specific NRA codes.

[9] I have created a measure of capacity utilization for motor vehicles industry by finding the ratio of output in particular year and maximum production in any prior year. I have created a measure of capacity utilization for cotton goods industry by finding the ratio of active spindles to total number of spindles in a particular year. In the cotton goods industry, this measure also varies by region. The assumption here is that once the capacity is built, it would not be destroyed. If an industry is not producing at maximum possible capacity then there is excess capacity in the industry.

3.3.2 Estimation

The first step in calculation of TFP is the estimation of the cost function. Following Christensen & Greene (1976), I estimate the cost function and the cost share equations jointly. This procedure results in higher efficiency in the estimation of the standard errors of the coefficients. In theory, the cost share equations do not contain disturbance terms as they are derived from the differentiation of the cost function, but I have specified additive disturbances for each of the share equations to capture changes in unobservable input prices. The disturbances are assumed to have a joint normal distribution. Additionally, the errors are assumed to be correlated across equations but not across observations within the same equation. To estimate the system of equations effectively, one equation is deleted. Use of an iterative maximum likelihood estimation procedure leads to estimates that are invariant to the equation dropped. The system of equations estimated after dropping capital share equation is:

$$\begin{aligned}\ln C^*_{st} = \alpha_0 + \sum_{i=1}^{4}\alpha_i \ln P_{ist} + \gamma \ln Y_{st} + \delta \ln T + \frac{1}{2}\sum_{i=1}^{4}\sum_{j=1}^{4}\alpha_{ij}\ln P_{ist}\ln P_{jst} + \frac{1}{2}\gamma^*(\ln Y_{st})^2 \\ + \frac{1}{2}\delta^*(\ln T)^2 + \sum_{i=1}^{4}\phi_i \ln T \ln P_{ist} + \sum_{i=1}^{4}\psi_i \ln Y_{st}\ln P_i + \theta \ln T \ln Y_{st} + \epsilon_{st}\end{aligned} \tag{3.21}$$

$$S_{wst} = S_1 = \alpha_1 + \alpha_{11}\ln P_1 + \alpha_{12}\ln P_2 + \alpha_{13}\ln P_3 + \alpha_{14}\ln P_4 + \psi_1 \ln Y_{st} + \phi_1 \ln T + \epsilon_{1st}$$

$$S_{sst} = S_2 = \alpha_2 + \alpha_{21}\ln P_1 + \alpha_{22}\ln P_2 + \alpha_{23}\ln P_3 + \alpha_{24}\ln P_4 + \psi_2 \ln Y_{st} + \phi_2 \ln T + \epsilon_{2st}$$

$$S_{mst} = S_3 = \alpha_3 + \alpha_{31}\ln P_1 + \alpha_{32}\ln P_2 + \alpha_{33}\ln P_3 + \alpha_{34}\ln P_4 + \psi_3 \ln Y_{st} + \phi_3 \ln T + \epsilon_{3st}$$

where,

S_{wst}= S_1 = wage share of total cost in state s in year t; S_{sst}=S_2= salary share of total cost in state s in year t; S_{mst}=S_3 = materials share of total cost in state s in year t; Y = output in state s in year t and T = Time trend. P_1= price of wage labor;

P_2= price of salaried labor; P_3= price of materials; and P_4= price of capital.

All these equations are subject to the restrictions specified in (2), (3), (4), (7), and (8). Some restrictions become redundant, as I have dropped the capital share equation. These equations are estimated as a system of seemingly unrelated equations using iterative maximum likelihood estimation. I consider two different versions of the model. The first version of the model includes prices for wage labor, salary labor, interest rates, material prices, output per establishment and a time trend. The time trend serves as a proxy for increases in technological change and is included in all the equations. This variable allows for changes over time in non-neutral efficiency, a change in production technology that does not result in a homothetic shift in the isoquant. The estimated coefficients on the time variables for each share equation give an estimate of the direction of the bias in efficiency gain as a result of technological change. The second version (full model) adds controls for regional effects[10] I have estimated five different models that take into account different time periods. Model I is estimated for all the years, 1919-39. Model II excludes the year 1919 and is estimated over the years 1921-39. I excluded year 1919 to take into account the changes in data reporting from year 1919 onwards. The Census of Manufactures excludes all establishments with a value of products falling below a certain minimum. Until 1919, the limit was \$500; for the years 1919 onwards the limit was changed to \$5,000.[11] This change in minimum between 1919 and 1921 is expected to result in a decline in coverage of the Census data. Hence, in Model II, I have excluded observations from 1919 to examine if the change in data coverage affected TFP estimates. Model III

[10]The TFP estimates from the model with regional effects and the model without regional effects are very similar. Hence, I have only reported results from the model with regional effects in the paper.

[11]For Census year 1921, data were collected for the number of wage earners and the value of products from establishments reporting products valued at more than $500 but less than 5000$. At prior Censuses, data on all subjects covered by the Census were secured from all establishments with products valued at more than \$500.

and model IV are estimated for years 1919-29 and 1929-39 respectively. We split the entire study period in two parts and estimate two different models to take into account the fact that the production function during the years 1919 to 1929 could have been different from the one in the years 1929 to 1939. By estimating two different models, I allow the parameters to be different over the two time periods. I estimate model V over the years 1921-29.

All the models are estimated using two different measures of the hourly wage rate and average wage rate.[12] Region fixed effects are included only in the cost equation and not in the share equation.[13] This assumption is equivalent to assuming that the coefficients on all of the left-out interaction terms are equal to zero. This implies a Hicks-neutral state and year impact. That is, the technical change affects all the inputs in the same way. TFP is calculated using the coefficients from Translog cost function estimation. The version of the model described in equation 3.9 gives us one measure of TFP. A more general measure of TFP can be calculated after estimating equations 3.14 and 3.15.[14] The Translog cost function does not put any restrictions on the structure of the production function. It does not require the production function to be homothetic or impose any restrictions on the elasticities of substitution. I

[12]For details on construction of measures of hourly wage rates, see the section on data and appendix B.

[13]We do not include region fixed effects in the share equations. To theoretically justify the inclusion of regional effects in the share equation, we need to include fixed effects-price interactions in the main cost equation. The addition of all of these interactive effects would quickly eat up the available degrees of freedom.

[14]Construction of a general index of technical change suffers from one main problem. Use of time dummies instead of a time trend increases the number of parameters to be estimated considerably as the Translog cost function requires inclusion of interactions of time dummies with input prices and output. I have 11 years of data and this leads to inclusion of fifty-five additional interaction terms. In order to reduce the number of parameters to be estimated we have experimented with few things. I have considered grouping years together, for example, pre-depression years, depression years and post-depression years. The problem with this approach is that it will not allow us to get an estimate of TFP change for each year separately. The system of equations given by equations 3.14 and 3.15 is subject to additional constraints given by equations 3.16 to 18. These constraints require that this system of equations be estimated as a non linear system of equations. We are in the process of exploring these possibilities.

have tested these restrictions statistically using the methodology adopted by Greene (2002). If the data fit the model with restrictions it is preferable to adopt the simplified model. I estimated two models in addition to the unrestricted Translog Model. Model B imposes homotheticity and Model C imposes homogeneity and then tests the hypotheses with a likelihood ratio test. [15] Equation 3.20 is estimated with Ordinary Least Squares.

The survey does not report the total cost of production. I used the total value of product as a measure of total cost. In long run equilibrium in competitive and monopolistic industries, the total economic cost and total revenue would be equal. The share left over after material costs, wage costs and salaried costs would be the share going to capital and the owner. The interest rate seems a good measure of the rate of return on capital and the owner's resources. In a monopolistic industry, the profit might well exceed the normal profits and thus there might be positive profits incorporated in the analysis. I have set output equal to value added. The missing observations are filled by interpolation.

I have made several assumptions for model specification and model estimation that are open to criticism. First, the crucial assumption in the estimation of the Translog cost function is that output and input prices are exogenous. I have industry level data at the state level and it is difficult to justify the assumption that output is exogenous because clearly firms are choosing their output levels. In the current

[15] The likelihood ratio test can be written as:

$$\lambda = -2(logL_r - logL_u) = T(log|\hat{W}_r| - log|\hat{W}_u|$$

where, T is the number of observations in each equation. $\hat{W}_r$ and $\hat{W}_u$ are the cross product matrices using the constrained and unconstrained estimators respectively. The test statistic is distributed asymptotically as χ^2 with degrees of freedom equal to the number of restrictions being imposed.

analysis output is assumed to be exogenous.[16] It is reasonable to assume exogenous input prices if I consider that a separate market exists for each input and no industry has monopsony power over labor. A number of studies surveyed by Boal & Ransom (n.d.) have found that monopsony power over labor markets is relatively rare in the U.S., even in industries like the coal industry in the early 1900s, which had been portrayed by labor historians as monopsonistic.

Second, since I have pooled all the cross sections for the four equations, there could be an additional problem of error interdependence overtime. This issue requires further exploration.

3.3.3 Data

I have separately estimated cost functions and constructed measures of TFP for eight industries: baking, boots and shoes (other than rubber), cotton goods, motor vehicles and parts, iron and steel (steel works and rolling mills), lumber and timber products, wholesale meatpacking and printing and publishing (newspapers and periodicals) utilizing state level information on these industries from the *Census of Manufactures* for the odd years between 1919 and 1939.[17] Table 3.4 reports the 20 largest industries ranked by the number of wage earners in 1929. I chose eight industries out of this list

[16]It is possible to work around this problem by finding instruments for output that are demand shifters and do not affect supply costs. For example, in case of baking industry candidates for instruments include population in the area. This is expected to be a good instrument because bread was often produced for local consumption. Bread is manufactured in every city and town of the country. As the bread becomes stale quickly, fresh bread must be sold the same day it is baked. Due to this reason the distribution of bakeries corresponds closely to that of population with the greatest concentration in the larger cities. Another potential instrument is the marked price of the output or the price of complements and substitutes. We can find similar instruments for the other industries.

[17]We are thankful to Joshua Rosenbloom for providing us with the data for years 1919 to 1937 from Rosenbloom and Sundstrom (1999), which provides details on data construction, coverage, and accuracy.

based on the availability of data. All the data are summary data for the manufacturing firms in that state. The survey reports data on three categories of inputs: cost of salaries, cost of wages, and cost of materials. It also contains data on the number of establishments, total people engaged in the industry, proprietors and firm members, salaried officers and employees, wage earners, and value of products.

The interest rate data is collected from state level bank loan interest rates compiled by Howard Bodenhorn. The price of materials is set equal to the wholesale price index or the retail price of the major input.[18] All the series are deflated to 1919 prices using the Consumer Price Index. The number of observations varies from industry to industry as all the industries did not have a presence in all the states or the Census did not provide information for some states. This was done to maintain the confidentiality of business establishments if there were very few firms in a given industry in a particular state. I have created a balanced panel for each industry. I have only retained the states that have less than twenty-five percent observations missing. I have filled missing observations by interpolation.

There are two types of labor input examined. The wages for salaried workers are calculated by dividing total salary earnings by the number of salaried workers reported in the Census statistics in each state and year. Several measures of wages are used as the price of labor. Hourly earnings are typically considered the best measure of the wage rate. Unfortunately, the Census of Manufactures does not report hourly wage rates by industry in most years during this period. Using information from the Bureau of Labor Statistics Labor Bulletins on Hours and Earnings and the Monthly Labor Review, I was able to construct two measures of hourly earnings that

[18]Wheat in case of baking industry; leather in case of boots and shoes; raw cotton in case of cotton goods; steel in case of motor vehicles and iron and steel; Douglas fir in case of lumber; beef steers in case of meatpacking and paper pulp in case of printing.

were consistently reported for many states and many years during the period. The measures are the hourly earnings of foremen and the hourly earnings of oven men from the baking (bread and other products) industry. I have referred to these two measures of hourly wage rate as hourly wage rate 1 (foremen hourly wage rate) and hourly wage rate 2 (ovenmen wage rate) respectively. It can be argued that foremen fall in the category of salaried workers rather than in the category of wage labor and hence it might be better to use hourly wage rate measure 2. I chose the bread industry to construct a measure of hourly wages because there was significant bread making in a large number of states over a long period of time and hence we get much more complete series as compared to other industries. I have also used measures of hourly wages for bread industry as a proxy for wages in other industries. The idea is that these hourly wages rates will be uncorrelated with the demand and supply shocks in that particular industry. We compared the hourly wage rates for baking industry with the hourly wage rates of other industries and reported the correlations in Table 3.5. We assumed that the bread hourly earnings are reasonable measures of the variations in wages in other industries across states and years as long as labor markets within a state have a strong degree of integration across industries. However, our correlation measures show very low degree of correlation between bread hourly wage rates and industry specific hourly wage rates. It is possible that a part of variation is hidden due to creation of a national average. I am in the process of comparing the variation in the bread wage rates with the small samples of hourly wage rates available through BLS across states and time in the other industries.

I have also estimated the model and calculated TFP using annual average earnings for wage workers-measured as total wages paid divided by the average number of wage workers – reported by the Census. Average annual earnings are usually more problematic than hourly earnings because they are a combination of hours worked and hourly wages and thus the hours worked component is a measure of labor input.

We find that the TFP estimates for various industries reported later in the paper are surprisingly very similar for all three measures of labor wage rates.

The data on strikes is collected from two sources. Data for the time period 1919-26 comes from *Monthly Labor Review*, July 1929.[19] Data for the time period 1927-1939 is collected from *Handbook of Labor Statistics*, 1947, bulletin 916. I have data on number of strikes for the entire time period by state. However, the data on number of workers involved in the strikes and man-days idled is available only for the years 1927-39. Data on annual production of passenger cars is collected from *Facts and Figures of the Automobile Industry*, National Automobile Chamber of Commerce, 1931 and 1934 (1919-1933) and Biennial Census of Manufactures, 1935 and 1939 (1935-1939). This data is used to construct the CAPACITY variable for motor vehicles industry.

3.4 Results

3.4.1 Trends in TFP

Table 3.6 shows the average share of each of the three inputs in the total costs for the eight industries. In all the eight industries, materials made up the largest portion of the total cost. Salaried labor had the smallest share in the total costs in all the industries except in printing. For the iron and steel industry wage labor comprised the biggest share of total costs and meatpacking industry spent the biggest share of its costs on materials. Table 3.7 reports the mean cost shares of inputs for four different time periods. This table allows us to track changes, if any, in input shares in pre-Depression, Depression and post-Depression years. The top panel shows that share of wage labor in the total costs did not suffer any decline in the Depression years, 1929-33 vis-a-vis years 1919-27. In fact, this time period witnessed an increase

[19] See Table 3, p.134.

in the share of wage labor in all industries except meatpacking and motor vehicles. Figures 3.1 - 3.6 track the changes in the shares of three inputs by year. Figures 3.1 and 3.2 also illustrate that there were no significant spikes and dips in the share of wage labor over time. However, all the industries showed an increase in the share of wage labor in year 1931 and most of the industries had a higher share of wage labor in 1939 as compared to 1919. The middle panel of Table 3.7 shows that the share of salaried labor in the total costs increased for all the industries in 1935-39 as compared to 1919-27 but there was no definite pattern of change over the depression years. Looking at Figures 3.3 and 3.4 we can observe that the iron and steel industry showed the most fluctuation over the study period. Also, six out of eight industries showed a dip in the share of salaried labor in 1933 and by 1939 all industries except cotton goods had a lower share of cost going to salaried workers. The last panel of Table 3.7 shows that on an average all industries reduced the amount that they spent on the materials in the years 1929-33. It is possible that the industries coped with the downturn by reducing the costs by cutting down the amount spent on materials or reduced production led to lesser amount being spent on materials. Figures 3.5 and 3.6 show that the share of materials in the total costs was lower for six out of eight industries in 1939 as compared to 1921. The analysis of input shares shows that in the industries studied there was a trend towards hiring more wage labor as compared to utilization of salaried labor and other inputs.

Five sets of biennial estimates of TFP for each of the eight industries are listed in Tables 3.10 - 3.27, Tables 3.30 - 3.32 and Tables 3.35 - 3.37. Model I is estimated using data for all the years: 1919-39. Model II excludes year 1919 and is estimated with data from years 1921 to 1939. Model III utilizes data from years 1919 to 1929 and Model V uses data from years 1929 to 1939. Model IV is estimated with data from years 1921 to 1929. The rationale for estimating these five different models is discussed in detail in Estimation section. We have also reported TFP measures that are estimated using three different measures of the wage rates. Three measures of wage rates that are utilized are: annual wage rate, baking industry foreman hourly wage rate and baking industry oven men hourly wage rate. All the models reported include regional effects. Table 3.4 shows the relative importance of these industries in the manufacturing industry in terms of wage labor employed by them. Six out of eight industries that we have studied are among the top ten industries in terms of wage earners.

I focus on the results from the model with hourly wage rate 2 here. I have also reported value added per man-hour in Table 3.9 and Kendrick's estimates in Table 3.8 for comparison purposes. The industries follow different patterns of TFP change. TFP estimates reported in Table 3.27 derived from models I-IV for printing and publishing industry show very small change in TFP overtime. All these four models show an increase in TFP over the years. However, model V shows declining TFP over the years 1929-39 and predicts TFP to be about 10 percent lower in 1939 as compared to 1929. We do not have any comparable measures of TFP from Kendrick for this industry. Table 3.9 shows that this industry experienced rising value added per man-hour over the time period 1919-35 except a dip in 1925.

TFP measures for the bread and other baking products industry and the boots and shoes industry reported in Tables 3.10 - 3.15 show very similar patterns of TFP change over time. For the bread and other baking products industry (Table 3.10) all the five models show an increase in TFP throughout the entire time period. TFP in 1939 was more than 5 percent higher than the TFP in 1929. A comparison with Kendrick's TFP estimates (see Table 3.8 and Figure 3.9) shows very similar TFP as estimated by our models. We observe the similar positive trend in TFP in Table 3.15 in the case of boots and shoes industry in all but model II. Model II indicates a decline in TFP in years 1931-33 followed by recovery in the late 1930s. Model V predicts

TFP in 1939 is 9.06 percent higher than in 1929, whereas model I predicts the TFP to be only 4.10 percent higher. Model I and model II predict a much smaller TFP change. This industry also experienced rising value added per man hour for most of this time period along with rising TFP.

Out of all the industries, iron and steel industry showed the largest fluctuations in TFP. This industry was also characterized by falling value added per man-hour in most of the years. As seen in Table 3.24, TFP in 1923 sunk 96 percent below its 1919 level, started recovering from 1925 and showed recovery until 1929. Iron and steel manufacturing TFP peaked again in 1933 before falling dramatically from 1933 through 1939. In contrast to the other industries, the magnitude of TFP change varied considerably over different models. However, both models I and II show that the level of TFP was much lower in this industry in 1939 as compared to 1920s. Model V, estimated over the years 1929-39 also shows recovery in TFP in years 1931 and 1933 before falling from years 1933 through 1937. In this case models III-V give much more reasonable estimates of TFP as compared to models I and II. Comparison with Kendricks' estimates given in Table 3.8 shows that Kendrick's finds very low TFP for this industry in 1919, whereas we estimate a very high TFP in 1919. TFP reported by Kendrick in 1937 at 90.2 is much more comparable to our estimate of 84.72.

The motor vehicles industry experienced declining TFP throughout the study period (Table 3.32) although value added per man-hour increased until 1931 before dipping in 1933 and again recovering by 1935 (Table 3.9). Meanwhile, as shown by Model I in Table 3.37 the cotton goods industry experienced a 11.46 percent decline in TFP between 1919 and 1929 before recovering slightly in 1937 and 1939. By 1939, TFP in this industry was still not back to its level in 1919. All the models show declining TFP in the 1920s and Model V shows significant decline even in 1930s. According to Model V, TFP was about 24 percent below its 1929 level in 1939.

The lumber and timber products and the meatpacking industries in Table 3.18 and Table 3.21 followed similar patterns. Each experienced a decline in TFP in 1923, 1935 and 1937. Both experienced increases in TFP in 1931, in the midst of the 1929-1933 drop. However, the lumber and timber industry had higher TFP in 1939 as compared to 1929 whereas the meatpacking industry had marginally lower TFP. Most of our TFP estimates for these two industries are not comparable to the ones constructed by Kendrick and reported in Table 3.8 and Figures 3.10 and 3.11. Only the estimated TFP for lumber and timber products for year 1937 at 106.2 is close to Kendrick's estimate of 102. Meatpacking industry showed a higher level of value added per worker in 1935 as compared to 1919 and 1929 (see Table 3.9).

The discussion of TFP at the industry-level provides us with the main conclusion that every industry followed a different path of TFP change. At least at the industry-level I do not find consistent evidence of a huge TFP decline for seven out of the eight manufacturing industries during the years 1929-33 as suggested by Ohanian (2001) and Cole & Ohanian (1999). Though most of the industries show a decline in TFP in 1929, in six industries out of eight the decline did not persist through 1933. I find mixed evidence on TFP recovery from year 1933 onwards. Four out of eight industries showed recovery. TFP estimates for these industries indicate that most of these industries suffered TFP decline in either 1933 or 1935 or in both the years. I do not find that 1930s were the period of interrupted TFP growth but I do find that five industries out of eight had higher productivity in 1930s as compared to 1920s. I also find that the TFP in these five industries had recovered by 1939 to its 1919 level. In contrast to Field's arguments about the rise in TFP during the Depression, I do not find large scale increases in TFP between 1927 and 1939 but I do find an upward trend in TFP of four industries in this time period. Overall, our analysis provides some evidence in favor of Field (2003) and Field (2005) rather than

Ohanian (2001) and Cole & Ohanian (1999). It should be noted, however, that these findings are confined to eight major manufacturing industries. The trends described by Ohanian (2001) and Cole & Ohanian (1999) may have occurred in other industries.

3.4.2 Motor Vehicles Industry and TFP

The motor vehicles industry was one of the most important industries in terms of economic significance during the first half of the century. As seen in Table 3.28, the industry started almost from scratch in 1900 and grew phenomenally to a peak production of over 4 million passenger cars by 1929. The Depression hit the industry hard, as car production fell below its 1919 level by 1933. As the economy recovered from 1933 through 1935 and the NRA codes were established, car production doubled and rose some more after the NRA codes were declared unconstitutional in 1935 to about 3.8 million cars in 1937. Production the sharply declined again between 1937 and 1939. Some have argued that the industry did well in the 1920s on the strength of one-time demand for a new product. As one of GM executives said, the success of the 1920s "could be attributed less to our own wits than to the improvement in the general economy and the rising demand for the automobiles". World War I had also led to rapid growth in consumer sales and commercial sales. About 41 percent of U.S. households owned a car by 1923 and the utilized capacity had fallen to 65 percent. After the end of the war, Ford and General Motors had worked at meeting the pent up consumer demand, but their expansions of production during the war period left them with problems of excess capacity (Gordon 1994).

One of the main features of this industry was limited competition. Early auto firms were just simple assembly plants that bought on credit from parts firms and sold for cash to dealers. Low capital requirements led to stiff competition. The leading firms developed economies of scale and used proprietary parts contracts and franchising agreements as tools for barring entry. The number of entrants that stood at 169 between 1902 and 1920 was reduced to 14 in 1923 and then 7 in 1930. Ford, GM (General Motors) and Chrysler emerged as the "Big Three" of automobile industry following the reorganization of the smaller firms. These firms accounted for 54 percent of the sales in 1917, 68 percent by 1921 and almost 90 percent by 1933. Most of the changes that were made in the automobile industry in 1920s were related to marketing rather than technical advances. These marketing features included experimentation with lower prices, promotion, trade-ins, model changes, option packages and credit installation plans (Gordon 1994).

This industry was also characterized by the payment of high wages. Since its period of early growth it had adopted a policy of high wages. As a result, the industry became very attractive for the thousands of workers from nearly all the states. Many workers came to Detroit and other Michigan communities at the direct solicitation of representatives of the automobile companies or as result of advertising placed in small town and rural areas. Michigan which was the center of the industry became the location of 70 percent of the employment in the industry. The industry had a particular seasonal pattern that had an effect on sales and production. There were two peaks in the cycle of demand for the automobiles: the natural spring buying peak and the peak incident to the introduction of new models. The model year started in January and ended with a shutdown period in November and December. The spring buying peak existed throughout the northeastern and north central United States. In spring about 70 percent of domestic automobile sales were made. The spring peak occurred due to improvement in weather conditions. The peak resulting from the introduction of new models, led to an increase of about 43 percent above the average for any month in which the model was introduced. Hence, the January auto fairs, the introduction of new models and the spring peak led to a very busy season. The seasonal pattern of sales and production contributed to a difference between the production during the low and high month of about 25 percent, which was substantially greater than in manufacturing as a whole.

The automobile industry was also highly sensitive to the business cycle. As seen in Table 3.28 the production of passenger cars fell sharply during short recessions in 1921, and 1927, and dramatically between 1929 and 1933 and 1937 and 1937. For example, the value of product of the automobile industry in 1929 declined from \$3,576, 645,000 in 1929 to \$987,000,000 in 1933.

In spring of 1933 just before the NRA was established, the industry was characterized by: heavy seasonal fluctuations, stagnation in the demand of automobiles, excess capacity, volatile employment, high wages and bias in the industry towards younger workers. When the National Industry Recovery Act (NIRA) was passed on 16 June, 1933, the significance of the automobile industry in the economy- it accounted for about 5 percent of total industrial production-led the Roosevelt administration officials to pressure the industry to formulate an NRA code. The code essentially operated by sanctioning and legalizing the trade practices that might have been considered a violation of the anti-trust rules if the industrial or trade associations agreed to new hour and wage provisions and also the right to collective bargaining. There were few enough firms and the industry paid high enough wages without unions that they did not necessarily consider the tradeoffs from setting up a code to be that attractive. The freedom from potential antitrust cases appears to have outweighed their anticipated losses from establishing labor standards, and they decided to formulate a code, which ran from August 1933 through May 1935. The automobile code did not include any fair trade practices; it was restricted to labor provisions - hour limitations, a minimum wage beneath the prevailing industry average and a guarantee of an open shop. Despite the large volatility of employment in the industry, the code did not specify any clauses dealing with employment volatility.

In setting the code the industry managers sought an open shop. The final code signed in August 1933 did not explicitly call for an open shop, but it was implicit in the language in the following clause: *employers in this industry may exercise their right to select, retain, or advance employees on the basis of individual merit, without regard to their membership or nonmember ship in any organization.* This merit clause remained in the Automobile code throughout the NRA. The automobile industry code was the only code that included such a clause. Similarly, other restrictions established in the code did not appear meaningful. For example, average hours worked were well below the code limit of 40 hours in the work week in both 1931 and 1933 (see Table 3.29 and (Fine 1963)). As a result the code of 1933 was not expected to cause any substantial changes in the industry in terms of employment volatility and hourly wages.

Table 3.30 - 3.32 show TFP for the Motor vehicle and parts industry. This industry is characterized by declining TFP throughout this time period. The 1920s experienced much higher TFP as compared to 1930s. However, the labor productivity measure reported in Table 3.9 shows increasing labor productivity throughout this time period. It is possible that the decline in TFP was coming from inputs other than labor. TFP fell 14.43 percent between 1919 and 1923 and then remained below its 1919 peak for every year between 1921 and 1939. As car production and employment peaked in 1929, TFP was 27.62 percent below its 1919 peak, possibly due to the rapid expansion in the hiring of new workers. TFP fell by 1.65 percent between 1931 and 1933, as the industry shed still more workers and reduced car production further. In 1935, TFP fell 37.10 percent below its peak in 1919 as the NRA code was instituted and employment, production, and hours worked rose sharply. By the end of the decade TFP still had not yet reached its 1919 peak and according to model I

and II TFP in 1939 was more than 15 percent below its 1929 level. Model V predicts TFP decline in 1930s to be even larger and estimates TFP in 1939 to be 50 percent lower than in 1929. We compared our TFP estimates with Kendrick's estimates reported in Table 3.8 and Figure 3.7. Kendrick's reported his TFP measures for only three years: 1919, 1929 and 1937, hence it is not possible to compare our estimates over the entire study period. Kendrick's estimates indicate the highest TFP in 1929, followed by 1927 and then 1919. We also find that 1929 had higher TFP than the 1930s but we do not find any evidence of very low TFP in 1919.

3.4.3 Cotton Goods Industry and TFP

The cotton goods industry was the largest branch of the textile industry. It employed slightly more than 1 person out of the every 20 persons engaged in manufacturing between the middle of the nineteenth century and the 1920s. In 1935, the number of establishments was no greater than it had been in 1850 but there were about 4 times as many wage earners and they were processing nine or ten times as much cotton (Hinrichs 1938).[20] However, cotton textiles had ceased to occupy a central position in manufacturing by the start of post first world war period (Szostak 1995).

By the time the Great Depression arrived, the cotton goods industry was already on decline. The peak profits in this industry were in 1923 while other industries boomed along to the heights of 1929 (Hinrichs 1938). Table 3.34 illustrates that the cotton goods industry, as measured by the value of products and value added, reached a peak in 1919 and then declined slowly through 1929 before a dramatic fall in 1931. The value of products increased again to slightly more than half the 1919 value by 1937 and then declined somewhat in 1939. Meanwhile, the number of wage

[20] A.F. Hinrichs was the chief economist for the Bureau of Labor Statistics and prepared the report on *Wages in Cotton-goods Manufacturing*.

earners peaked in 1923 and the number of spindles peaked in 1927 (Table 3.33). In 1919 the industry accounted for 3.4% of all manufactures, measured both by value of products and by value added. But twelve years later it had dropped to 1.9% by value of product and 2% by value added. Backman & Gainsbrugh (1946) noted declining importance of this industry and said that "Within less than a generation, this industry has found itself struggling for existence against a rising tide of liquidation, bankruptcies, reorganizations, and losses."

The declining importance of the cotton goods sector can be explained by several factors. The market for cotton goods is highly dependent upon the income levels of the population. As incomes rose in the 1920s, the average per capita consumption of cotton goods rose from 25.6 pounds in 1920-24 to 27.6 pounds in 1925-29. However, the drop in income during the Great Depression led to a decline in cotton goods consumption to 21.4 pounds of cotton per capita on average over the period from 1930 to 1934 (Hinrichs 1938).[21]

In general, cotton goods consumption responded to factors other than the income change. In fact, data collected by Szostak (1995) shows that expenditure on clothing rose barely 5 percent between 1923 and 1929, much more slowly than the increases in population and in income per capita. The demand was quite inelastic in this time period and indicated that society had reached a point when people were relatively satisfied with their consumption of cotton goods and the demand for the cotton goods had stabilized (Szostak 1995). The situation was further exacerbated by changes in tastes and increased competition from rayon and the paper industry. The paper industry substituted the cotton goods industry in the production of towels, napkins,

[21] D.Wandersee (1981) pointed to the fact that while people were hesitant to cut back on food or housing in the Depression, significant cuts were made in expenditures on clothing. Wolfman (1929) also recounted that expenditure on clothing had declined overtime.

bags and bandages. The producers were not able to expand output even by slashing prices in the cutthroat competition of the late 1920s.

Faced with intense competition and declining markets, the producers in this industry could maintain their profit margins either by cost cutting or by finding new ways of increasing productivity. Cost cutting was very important in this industry because the cotton goods industry was highly competitive, as were many of the textile industries. As demand slowed for cotton goods, the industry sought new ways to cut costs. One of the cost cutting measures adopted by the industry was to - shift more of its production from North to South, where wages and taxes were lower, and there was easy access to raw materials, and water power. I do not have data that reports production of cotton goods for each year over the time period 1919-39. However, the data on wage earners, value of products and value added shows the shift from North to South (see Figures 3.12- 3.14). Figure 3.12 shows that in the North, employment (measured by the number of wage earners) declined to about half over the time period 1919 to 1939 and it more than doubled in the South over the same period, though the total employment showed only a marginal increase over this time period. Figure 3.13 and 3.14 illustrate that this time period also witnessed an increase in value of products and value added in the South and a decline in same in the North.

The increase in productivity was mainly attained by speeding up the production process or through automation. The producers adopted methods of scientific management in order to improve productivity and improve quality. The companies made more extensive use of long-staple cotton and improved their processing in the carding department and on the spinning frames (Hinrichs 1938). Bernstein (1960) describes that the mills strove to capture an increasing share of a decreasing market by forcing their workers to work harder. Industry changed over very rapidly from one-shift to two-shift and to some extent to three-shift operations. As a result, measures of the productivity of capital rose during the 1920s and 1930s. The number of spindle hours required to process a bale of cotton decreased from 15,300 in 1922-23 to 12,700 by 1936-37. Additionally, active spindles averaged 2945 hours per year in 1922-23 whereas they averaged 4183 in 1936-37; an increase of 42 percent. The average number of spindle hours required to process a pound of cotton, as a result, fell from 28.73 for the five-year period August 1923-28 to only 25.84 hours for the five years from August 1933-38. Though there was an increase in the productivity of active spindles, the number of idle spindles had been on a rise from 1923 (Backman & Gainsbrugh 1946). This led many producers to complain of over expansion and chronic excess capacity in the post world war era.

Table 3.33 demonstrates that the number of inactive spindles had been on rise throughout 1920s and until mid 1930s. The number of inactive spindles began to decrease from 1935 and the decline continued till 1939. However, an increase in excess capacity was not accompanied by a decline in the employment due to significant labor hoarding. Table 3.33 and Table 3.34 show that the employment (number of wage earners) fell by only 8 percent between the years 1919 and 1939 where as value added fell by 23 percent over the same time period. The comparison of value added per worker and value added per spindle shows that they started at about the same level in 1919 but by 1939, the index of value added per spindle at 145.56 was much higher than value added per worker at 118.29. Lower productivity per worker could have been a result of labor hoarding.

The textile industry in this time period benefitted significantly from improvements in machinery and equipment and use of electricity. Improvements in machinery took place in the three basic processes in the industry, carding, spinning and weaving, so that speeds were increased and operations were made smoother. Electric motors were first applied to the textile machinery in 1890s. By the mid-1920s about 1.5 million horsepower of electric motors were used in the cotton goods industry and by 1939 the number had increased to 1.7 million horsepower of electric motors. The use of electric power facilitated the location of mill at the most favorable spot. The use of electric power also led to great improvement in the machine work and in the precision applied to textile machinery. According to Bernstein (1987) these technological changes in the industry led to an increase in labor productivity and output per worker rose 82.4 percent between 1919 and 1940. Our TFP estimates do not support Bernstein and show declining TFP between 1919 and 1939.

Table 3.35 - 3.37 report TFP for the cotton goods industry. Measures of TFP are similar for all the three different measures of wage rates. However, TFP differs over the five models. I have focused on TFP measure developed by using hourly wage rate 2 for the discussion of results (Table 3.37). Models I and II show that TFP fell by more than 5 percent between 1921 and 1929 and it remained below its 1921 level throughout the 1930s. Model III, estimated over the time period 1919-29 and Model IV estimated over the time period 1921 - 1929 also show a decline in TFP between 1921 and 1929. However, Model III indicates a much smaller decline in TFP (about 2.87 percent) as compared to Model IV (about 10 percent). Model V shows a much larger decline in TFP in 1930s as compared to models I and II. According to this model, TFP in 1939 was 24 percent lower than in 1929. All these models, despite differences in magnitude of decline in TFP, indicate that the cotton goods industry suffered from declining TFP in 1930s and never attained the level of TFP it enjoyed in 1920s. The decline in TFP could have occurred due to excess capacity build up in this industry. A rise in excess capacity is indicated by an increase in the number of idle spindles particularly in 1920s (Table 3.33). Still, a long-range downturn in total factor productivity is puzzling given the technological improvements, cost cutting measures and increased use of electric motors. One can conjecture that TFP decline is caused by a shift in geography, that is, shift in production from high TFP

states to low TFP states. Figure 3.15 shows that the TFP was higher in the North as compared to the South. It is possible that the shift was occurring at a faster pace than the improvements in this industry and kept the TFP depressed.

I have reported regression results for equation 3.20 estimated for motor vehicles industry in Table 3.38 and estimation results for cotton goods industry in Table 3.39. This equation aims to identify the main factors contributing to TFP changes in the cotton goods industry. The tables report elasticity and one unit standard deviation along with parameter estimates. Explanatory variables are included to measure employment, change in output, strikes, and capacity utilization rates. Year dummies are included to capture the effects of the introduction of the NRA as well as other national shocks to the industry. I am in the process of including electricity usage and major technological changes in my analysis.

I have included the **STRIKE** variable to determine the impact of work stoppages on TFP. Strikes potentially lowered TFP due to the costs of ending and restarting the production process at the beginning and ending of the strike. TFP would be damaged further by longer term damage to industrial relations between workers and employers arising from events leading up to the strike or during the strike, particularly violence that caused workers to reduce their effort. Additional costs arose if skilled workers left during the strike and were replaced by workers who required new training. These effects would be mitigated somewhat if the plant could build inventories in advance of the strike at no extra cost. The results reported in Tables 3.38 and 3.39 show that strikes had a statistically significant negative relationship with TFP for both the industries. To some extent the strike activity can be attributed to the increased rights of unions to engage in collective bargaining associated with the National Industrial Recovery Act of 1933 and the National Relations Act of 1935. These acts led many workers to join unions and engage in strikes to establish the unions as their bargaining agents. Strike days increased to 14 million in 1936 and 28 million in 1937 (Cole & Ohanian 2005) after the NLRA (National Labor Relations Act) was passed. Still, one unit standard deviation effects of the **STRIKE** variable on TFP are very small in both the cases. A one standard deviation decrease in **STRIKE** yields only a 0.015 standard deviation increase in the predicted TFP for cotton goods industry and only a 0.017 standard deviation increase in case of motor vehicles industry. Part of the problem could be measurement error because this is strike activity in the state as a whole, not by industry.

EMPLOYMENT, the number of workers employed by the industry, is expected to be associated with reductions of TFP if expansions in employment required the firms to hire inexperienced workers that would require training. The regression results show a negative and statistically significant relationship between TFP and employment for both the industries, consistent with this expectation. To the extent that the NRA code led the cotton goods industry and motor vehicles industry to increase employment by hiring new workers, part of the impact of the NRA might have come through this variable as well. However, again as in the case of **STRIKE** variable, one unit standard deviation is pretty small.

Gordon conjectured that motor vehicles industry suffered declining TFP due to unutilized capacity. There is anecdotal evidence that discusses an increase in idle spindles and build up of excess capacity in cotton goods industry as well. Inclusion of the **CAPACITY** variable as a regressor allows us to test the conjecture that both the industries faced declining TFP due to excess capacity. The **CAPACITY** variable is constructed as a ratio and measures capacity utilization in the industry. A value closer to one indicates higher utilization of capacity in the industry. I expect this variable to be positively correlated with TFP, indicating that higher capacity utilization led to higher TFP. The results show that the capacity utilization variable is statistically significant at the one percent level of significance and is positively related to TFP growth in the motor vehicles industry. This result provides evidence in favor of Gordon's conjecture that excess capacity was one of the reasons behind declining productivity in case of motor vehicles industry. To the extent that the NRA code led the firms to reduce their production and thus capacity utilization, the NRA could have been partially responsible for the consequent reduction in TFP. However, in the case of cotton goods industry we find that the capacity utilization variable is statistically significant but is negatively related to TFP growth. This result is counter-intuitive and at odds with our conjecture that excess capacity was responsible for declining TFP.

After controlling for the effects of capacity utilization, strikes, and employment, the 1933 and 1935 year effects capture unmeasured aspects of the NRA as well as macroeconomic shocks that might have influenced TFP. The NRA code for cotton goods industry was approved on 9 July, 1933. The main aim of the code was to deal with over-capacity and restore "fair" competition in the industry. Supporters of the NRA code argued that over-capacity and the ever-present threat of over-production led sellers to scramble in order to secure volume, resulting in price cutting without any regard to costs. This price-cutting led employers to pressure wage - earners to accept lower wages so that the plant can secure new orders and keep plant operating.

The code had three main provisions. First, the maximum hours of work per week were shortened so that more workers could stay employed, albeit with fewer hours of work for each. Second, a floor was fixed for hourly wages so that workers' wages would fall no further. Third, the effective productive capacity of the industry was reduced by putting a limit upon the hours of operation of its productive machinery to restore balance between supply and demand. The first two provisions meant substantial increase in costs and would not have rehabilitated the industry without the third provision. The main aim of the third provision was to increase the profits in the industry and reduce price competition in the industry. The Code could have affected TFP through several channels. First, the NRA was designed to keep employed workers at work while spreading the work over more workers. This provision implied that instead of laying off the less productive workers and giving more hours to more productive workers, firms were now expected to keep all workers and share working time. This labor hoarding could have resulted in reduced labor productivity. On the other hand, by keeping workers around the firm could have reduced training costs in future years. The NRA could have also led to building of excess capacity by limiting the hours of operation. The year effects in Table 3.38 - 3.39 show a positive effect in both the years 1933 and 1935 as compared to base year 1919.

3.5 Concluding Remarks

The main aim of this paper is to study the evolution of the productivity over the years 1919 to 1939. To this end, I have conducted analysis in two stages. In the first stage, I estimate TFP econometrically for eight industries using a Translog cost function estimation technique. These TFP estimates help me to identify the industries that were leaders in TFP growth and also help resolve the conflicting picture of TFP offered by Ohanian (2001), Field (2003), and Field (2005). In the second stage, I use a regression framework to identify the factors that can explain the changes in TFP over time.

My main conclusion regarding trends in TFP is that each industry followed a separate path of TFP change. I do not find consistent evidence on huge TFP decline during the years 1929-33 and then a sharp rise from 1933 through 1939, as suggested by Ohanian (2001) and Cole & Ohanian (1999). I do not find evidence of the large-scale increase proposed by Field (2003) and Field (2005) for the period 1927 through 1941 but I do find that five industries out of eight were characterized by higher productivity in 1930s as compared to 1920s. It should be noted, however, that my analysis is restricted to eight major manufacturing industries, and the dramatic changes in TFP described by prior authors may have occurred in other industries or other sectors of the economy.

Analysis of the motor vehicles industry and cotton goods industry reveals that increases in employment and strikes were associated with reductions in TFP. The NRA codes in place between 1933 and 1935 gave firms and workers the types of incentives that led to these kinds of changes; therefore, the NRA may have indirectly contributed to reductions in TFP. On the other hand the year effects for 1933 and 1935 are consistent with the hypothesis that unmeasured aspects of the NRA might have contributed to an increase in TFP these years.

Table 3.1. Sectoral Productivity and Compositional Shifts in Production

Sector	**TFP**	**1933 Labor**
Manufacturing	91.5	59.7
Farming	104.5	97.4
Mining	99.5	55.2
Railroads	90.2	51.3
Communications	100.9	62.1

Source: Ohanian (2001),'Why Did Productivity Fall so much during the Great Depression' table 2, p. 35. TFP is reported as the relative productivity in 1933, as a percentage of that in 1929. The "1933 Labor" reports sectoral employment in 1933, as a percentage of that in 1929.

Table 3.2. Sectoral Productivity and Compositional Shifts in Production

Year	**Real Output**	**Business Investment**	**Total Employment**	**Labor Productivity**	**TFP**
1929	100	100	100	100	100
1930	87.3	69.2	93.2	95.9	94.8
1931	78.0	46.1	85.7	95.4	93.5
1932	65.1	22.2	77.5	90.7	87.8
1933	61.7	21.8	76.2	87.9	85.9
1934	64.4	27.9	79.9	96.7	92.6
1935	67.9	41.7	81.4	98.4	96.6
1936	74.7	52.6	83.9	101.6	99.9
1937	75.7	59.5	86.4	100.7	100.5
1938	70.2	38.6	80.4	102.4	100.3
1939	73.2	49.0	82.1	104.6	103.1

Source: Cole and Ohanian (1999), 'The Great Depression in the United States from a Neoclassical Perspective', Table 2, p. 5 and Table 6, p. 9.

Table 3.3. Compounded Annual Average Growth Rates of MFP, US, 1919-1948

Year	**Solow (Private Non-Farm Economy)**	**Kendrick (Private Domestic Economy)**	**Kendrick (Private Non-Farm Economy)**
1919-1929	0.78	1.97	2.02
1929-1941	2.36	2.27	2.31
1941-1948	0.89	1.51	1.29

Source: Field (2003), 'The Most Technologically Progressive Decade of the Century', Table 2, p. 1404.

Table 3.4. Top Twenty Manufacturing Industries in 1929, Ranked by Employment

Rank	**Industry**	**No. of Wage Earners**	**Sample Employment**	**Proportion Covered**
1	Foundry and machine-shop products	454,441		
2	Motor Vehicles and Parts	447,448	425,354	0.951
3	Cotton goods	424,916	411,977	0.97
4	Lumber and Timber Products	419,084	418,539	0.999
5	Iron and Steel	394,574	369,197	0.936
6	Car and general construction and repairs, steam RR	368,681		
7	Electrical Machinery	328,722		
8	Knit Goods	208,488		
9	Boots and Shoes other than rubber	205,640	202,608	0.985
10	Bread and Other Bakery Products	200,841	199,495	0.993
11	Furniture	193,399		
12	Clothing, womens	187,500		
13	Printing and publishing, book and job	150,649		
14	Clothing, mens	149,868		
15	Silk and rayon	130,647		
16	Printing and publishing, newspapers and periodicals	129,660	128,315	0.99
17	Meatpacking, wholesale	122,505	119,032	0.972
18	Cigars and cigarettes	105,308		
19	Paper	103,320		
20	Canning and preserving	98,866		

Source: This table is reproduced from Rosenbloom and Sundstrom (1999), Table 2, p. 722. The data is from U.S. Department of Commerce, Bureau of the Census, Fifteenth Census of the United States, Manufactures: 1929, table 6.

Table 3.5. Correlation between National Average Industry Specific Hourly Wages and Bread Hourly Wages

Industry	Foremen Wages	Ovenmen Wages
Automobiles	0.439	0.3955
Boots and Shoes	0.2532	0.1915
Cotton Goods	0.0574	0.0784
Iron and Steel	0.3884	0.3172
Lumber and Timber Products	0.205	0.1643
Meatpacking	0.4219	0.3782
Printing	0.277	0.2672

Table 3.6. Mean Cost Shares of Inputs for Eight Industries

Industry	Wage Labor	Salaried Labor	Materials
Bread and Baking Products	0.183	0.028	0.509
Boots and Shoes	0.242	0.041	0.535
Cotton Goods	0.233	0.024	0.566
Iron and Steel	0.22	0.04	0.605
Lumber and Timber	0.331	0.046	0.382
Meatpacking	0.054	0.026	0.854
Motor Vehicles and Parts	0.159	0.03	0.638
Printing	0.158	0.171	0.256

Table 3.7. Mean Cost Shares of Inputs for Eight Industries for Different Time Periods

Wage Labor				
Industry	**1919-27**	**1929-33**	**1935-39**	**1929-39**
Bread and Baking	0.168	0.198	0.191	0.195
Boots and shoes	0.231	0.246	0.256	0.251
Cotton Goods	0.217	0.246	0.249	0.247
Iron and Steel	0.215	0.224	0.225	0.225
Lumber and Timber	0.334	0.336	0.323	0.329
Meatpacking	0.057	0.044	0.06	0.052
Motor Vehicles	0.162	0.151	0.163	0.157
Printing	0.153	0.157	0.167	0.162
Salaried Labor				
Industry	**1919-27**	**1929-33**	**1935-39**	**1929-39**
Bread and Baking	0.028	0.03	0.028	0.029
Boots and shoes	0.044	0.042	0.036	0.039
Cotton Goods	0.022	0.027	0.023	0.025
Iron and Steel	0.044	0.041	0.034	0.038
Lumber and Timber	0.044	0.055	0.04	0.047
Meatpacking	0.021	0.043	0.016	0.03
Motor Vehicles	0.033	0.029	0.025	0.027
Printing	0.174	0.17	0.168	0.169
Materials				
Industry	**1919-27**	**1929-33**	**1935-39**	**1929-39**
Bread and Baking	0.54	0.458	0.507	0.483
Boots and shoes	0.547	0.522	0.528	0.525
Cotton Goods	0.581	0.548	0.559	0.553
Iron and Steel	0.627	0.593	0.582	0.588
Lumber and Timber	0.393	0.347	0.396	0.372
Meatpacking	0.863	0.839	0.852	0.846
Motor Vehicles	0.628	0.615	0.677	0.646
Printing	0.291	0.207	0.245	0.226

TABLE 3.8. Total Factor Productivity Measures from Kendrick

Industry	**1919**	**1929**	**1937**
Motor Vehicles	35.9	100	98.3
Iron and Steel	57.7	100	90.2
Bread and Other Bakery Products	80.6	100	105.9
Meatpacking	71	100	115.2
Lumber and Timber Products	75.1	100	102

Source: Productivity Trends in the United States by John W. Kendrick, Table D-VI, Pages 483-86.

TABLE 3.9. Labor Productivity (Value Added per Man-Hour, 1929=100)

Year	**Value Added per Man-Hour**					
	Motor Vehicles	**Iron and Steel**	**Baking**	**Printing**	**Meatpacking**	**Boots and Shoes**
1919	81.59	84.69	88.85	70.51	80.72	103.18
1921	81.99	59.39	64.6	84.86	78.73	92.11
1923	85.15	79.79	84.99	86.47	84.92	94.10
1925	94.78	82.13	79.77	77.87	94.77	92.90
1927	94.89	73.97	82.43	91.77	86.7	99.92
1929	100.00	100.00	100.00	100.00	100.00	100.00
1931	109.00	84.30	90.82	105.56	99.92	105.19
1933	102.19	80.45	102.04	107.62	97.41	101.09
1935	108.64	132.47	102.29	119.86	118.82	111.15

Sources: Data on value added is from Census of Manufactures; Data on average actual hours per week per wage earner is from Wages, Hours, and Employment in the United States 1914-1936 by M. Ada Beney.

TABLE 3.10. Total Factor Productivity for *Bread and other Bakery Products* Industry (Annual Wage Rate)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	88.04		79.30		
1921	90.31	91.18	83.23	77.83	
1923	92.87	93.56	87.79	82.2	
1925	94.95	95.38	91.33	87.15	
1927	97.57	97.78	95.53	90.93	
1929	100.00	100.00	100.00	100.00	100.00
1931	101.53	101.36			99.36
1933	102.39	102			99.03
1935	104.51	103.86			100.15
1937	107.02	106.14			100.96
1939	108.94	107.54			101.00
N	528	480	288	240	288

TABLE 3.11. Total Factor Productivity for *Bread and other Bakery Products* Industry (Hourly Wage Rate 1)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	91.56		79.96		
1921	92.96	92.99	83.75	78.19	
1923	94.75	94.83	88.14	82.46	
1925	96.33	96.34	91.65	87.45	
1927	98.29	98.27	95.69	91.11	
1929	100	100	100	100	100
1931	100.79	100.84			100.58
1933	101.01	101.03			101.67
1935	102.49	102.45			104.01
1937	104.51	104.42			105.72
1939	105.35	105.19			106.1
N	528	480	288	240	288

Table 3.12. Total Factor Productivity for *Bread and other Bakery Products* Industry (Hourly Wage Rate 2)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	91.32		78.66		
1921	92.80	93.00	82.84	77.65	
1923	94.65	94.85	87.62	82.05	
1925	96.23	96.32	91.17	87.06	
1927	98.26	98.28	95.42	90.81	
1929	100.00	100.00	100.00	100.00	100.00
1931	100.76	100.85			100.81
1933	100.91	101.04			102.34
1935	102.42	102.5			104.88
1937	104.49	104.48			106.42
1939	105.23	105.21			106.77
N	528	480	288	240	288

Table 3.13. Total Factor Productivity for *Boots and Shoes* Industry (Annual Wage Rate)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	97.20		99.40		
1921	97.61	96.51	98.84	98.74	
1923	98.50	97.86	99.10	99.00	
1925	98.82	98.47	99.00	99.23	
1927	99.29	99.28	99.28	99.81	
1929	100.00	100.00	100.00	100.00	100.00
1931	100.39	96.97			101.40
1933	101.22	97.56			103.29
1935	102.03	98.44			105.06
1937	102.58	99.37			106.33
1939	103.10	100.12			107.70
N	220	200	120	100	120

Table 3.14. Total Factor Productivity for *Boots and Shoes* Industry (Hourly Wage Rate 1)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	97.00		94.89		
1921	97.36	97.05	95.25	93.75	
1923	98.37	98.28	96.63	94.57	
1925	98.86	98.80	97.57	96.35	
1927	99.48	99.50	98.67	97.54	
1929	100.00	100.00	100.00	100.00	100.00
1931	100.11	97.61			101.88
1933	100.56	98.00			103.68
1935	101.28	98.67			105.40
1937	102.08	99.47			107.08
1939	102.74	100.13			108.55
N	220	200	120	100	120

Table 3.15. Total Factor Productivity for *Boots and Shoes* Industry (Hourly Wage Rate 2)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	96.49		95.39		
1921	97.00	96.09	95.98	96.08	
1923	98.02	97.52	97.10	97.14	
1925	98.60	98.28	97.69	97.95	
1927	99.22	99.17	98.52	99.14	
1929	100.00	100.00	100.00	100.00	100.00
1931	100.62	96.41			101.87
1933	101.59	97.25			104.18
1935	102.54	98.26			106.09
1937	103.30	99.26			107.52
1939	104.10	100.19			109.06
N	220	200	120	100	120

Table 3.16. Total Factor Productivity for *Lumber and Timber* Industry (Annual Wage Rate)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	106.54		111.06		
1921	108.74	96.87	113.33	108.04	
1923	101.63	94.00	101.02	98.38	
1925	101.41	96.64	99.61	97.61	
1927	101.62	99.35	100.31	99.02	
1929	100.00	100.00	100.00	100.00	100.00
1931	103.96	105.02			100.75
1933	104.35	106.46			100.77
1935	101.30	104.67			99.63
1937	98.25	103.22			98.32
1939	98.10	104.28			98.05
N	462	420	252	210	252

Table 3.17. Total Factor Productivity for *Lumber and Timber* Industry (Hourly Wage Rate 1)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	101.01		107.38		
1921	104.22	98.47	111.81	117.55	
1923	98.62	95.30	98.74	101.11	
1925	99.38	97.40	98.12	99.20	
1927	100.53	99.58	99.81	100.27	
1929	100.00	100.00	100.00	100.00	100.00
1931	105.13	105.11			100.49
1933	106.70	106.78			100.19
1935	105.11	105.5			98.77
1937	103.24	104.23			97.41
1939	104.07	105.27			97.11
N	462	420	252	210	252

Table 3.18. Total Factor Productivity for *Lumber and Timber* Industry (Hourly Wage Rate 2)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	99.63		107.36		
1921	104.13	98.44	109.62	113.31	
1923	97.00	94.16	100.10	102.24	
1925	98.57	96.82	99.07	100.27	
1927	100.51	99.57	99.93	100.53	
1929	100.00	100.00	100.00	100.00	100.00
1931	107.11	106.56			100.76
1933	110.17	109.53			100.64
1935	108.33	108.23			99.31
1937	106.11	106.76			97.95
1939	108.19	108.87			97.65
N	462	420	252	210	252

Table 3.19. Total Factor Productivity for *Meatpacking* Industry (Annual Wage Rate)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	96.07		82.54		
1921	99.19	103.38	88.85	83.91	
1923	96.54	100.16	89.16	89.11	
1925	99.21	100.99	95.82	85.72	
1927	101.04	101.81	100.06	108.14	
1929	100.00	100.00	100.00	100.00	100.00
1931	101.71	101.38			100.37
1933	100.54	100.61			101.90
1935	100.09	99.71			100.17
1937	99.12	98.34			97.97
1939	99.22	97.93			96.87
N	374	340	204	170	204

Table 3.20. Total Factor Productivity for *Meatpacking* Industry (Hourly Wage Rate 1)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	95.39	102.26	78.03		
1921	98.46	103.86	85.14	114.41	
1923	96.40	100.75	86.65	104.83	
1925	99.08	101.62	94.67	135.54	
1927	100.92	102.01	99.68	120.31	
1929	100.00	100.00	100.00	100.00	100.00
1931	101.80	100.70			100.55
1933	101.30	99.69			99.42
1935	101.15	98.60			98.62
1937	100.55	97.08			97.04
1939	100.92	96.43			96.77
N	374	340	204	170	204

Table 3.21. Total Factor Productivity for *Meatpacking* Industry (Hourly Wage Rate 2)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	96.08		88.19		
1921	98.81	101.97	92.30	97.56	
1923	96.38	99.11	91.00	94.96	
1925	99.17	100.72	97.04	87.63	
1927	100.90	101.47	100.46	117.43	
1929	100.00	100.00	100.00	100.00	100.00
1931	101.41	100.51			101.84
1933	100.25	98.84			101.31
1935	99.98	97.80			102.58
1937	99.32	96.39			103.24
1939	99.64	95.82			104.89
N	374	340	204	170	204

Table 3.22. Total Factor Productivity for *Iron and Steel* Industry (Annual Wage Rate)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	145.64		106.48		
1921	159.48	201.30	115.13	96.24	
1923	105.59	95.66	97.50	85.24	
1925	105.09	100.28	99.51	90.89	
1927	106.14	107.47	102.06	97.32	
1929	100.00	100.00	100.00	100.00	100.00
1931	110.88	123.44			144.66
1933	111.31	129.91			192.41
1935	94.41	104.09			197.54
1937	78.62	79.15			207.14
1939	80.89	86.36			268.30
N	121	110	66	55	66

Table 3.23. Total Factor Productivity for *Iron and Steel* Industry (Hourly Wage Rate 1)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	118.19		89.54		
1921	131.02	232.39	98.77	81.78	
1923	97.79	99.86	89.50	90.82	
1925	99.48	103.55	93.88	84.93	
1927	102.58	109.53	98.54	90.31	
1929	100.00	100.00	100.00	100.00	100.00
1931	110.07	123.77			125.51
1933	110.45	125.99			121.17
1935	100.47	94.70			82.80
1937	90.59	70.16			54.35
1939	94.73	78.06			61.09
N	121	110	66	55	66

Table 3.24. Total Factor Productivity for *Iron and Steel* Industry (Hourly Wage Rate 2)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	198.29		98.64		
1921	249.23	495.85	110.25	86.25	
1923	102.97	105.12	92.38	97.65	
1925	105.24	109.29	96.12	85.37	
1927	110.35	116.76	100.53	91.03	
1929	100.00	100.00	100.00	100.00	100.00
1931	122.61	134.43			147.12
1933	123.6	139.1			150.62
1935	93.46	87.04			111.17
1937	69.24	53.36			84.72
1939	76.12	61.76			113.74
N	121	110	66	55	66

Table 3.25. Total Factor Productivity for *Printing and Publishing (Newspapers and Periodicals)* Industry (Annual Wage Rate)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	100.12		96.90		
1921	99.93	99.81	97.67	102.08	
1923	99.69	99.58	98.18	102.22	
1925	99.68	99.56	98.78	101.65	
1927	99.87	99.81	99.42	101.27	
1929	100.00	100.00	100.00	100.00	100.00
1931	100.68	100.77			100.28
1933	101.09	101.23			100.49
1935	101.69	101.97			100.32
1937	102.12	102.47			99.91
1939	102.89	103.24			100.17
N	528	480	288	240	288

TABLE 3.26. Total Factor Productivity for *Printing and Publishing (Newspapers and Periodicals)* Industry (Hourly Wage Rate 1)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	98.46		94.56		
1921	98.52	99.95	95.84	102.68	
1923	98.65	99.69	96.83	102.67	
1925	98.97	99.65	97.89	101.92	
1927	99.51	99.86	98.97	101.35	
1929	100.00	100.00	100.00	100.00	100.00
1931	101.02	100.72			98.17
1933	101.95	101.33			96.57
1935	102.98	102.08			94.71
1937	103.85	102.67			92.85
1939	104.86	103.43			91.78
N	528	480	288	240	288

TABLE 3.27. Total Factor Productivity for *Printing and Publishing (Newspapers and Periodicals)* Industry (Hourly Wage Rate 2)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	99.08		94.74		
1921	99.03	100.36	95.90	103.44	
1923	99.01	99.98	96.86	103.22	
1925	99.19	99.81	97.90	102.36	
1927	99.62	99.92	98.98	101.66	
1929	100.00	100.00	100.00	100.00	100.00
1931	100.9	100.61			97.96
1933	101.55	100.93			96.08
1935	102.41	101.53			94.03
1937	103.07	101.92			91.98
1939	103.95	102.51			90.73
N	528	480	288	240	288

Table 3.28. Production and Growth Rates of Automobiles from 1904-1939

Year	No. of Passenger Cars	Annual Percentage Growth
1904	22419	99.60
1919	1657652	75.70
1921	1518061	-19.70
1923	3753945	58.40
1925	3870744	17.20
1927	3083360	-22.00
1929	4794898	19.50
1931	2038183	-30.00
1933	1627768	37.00
1935	3212835	97.00
1937	3849576	16.50
1939	2824203	-26.60

Sources: Facts and Figures of the Automobile Industry, National Automobile Chamber of Commerce, 1931 and 1934 (1904-1933); Biennial Census of Manufactures, 1935 and 1939 (1935-1939).

Table 3.29. Wage Earners and Average Hours Worked, 1919-1939

Year	**Wage Earners**	**Avg. Hours Worked per week**	**Index of Employment (1929=100)**	**Index of Hours Worked (1929=100)**
1919	343115	45.9	76.68	98.08
1921	212777	44.7	47.55	95.51
1923	404886	47.7	90.49	101.92
1925	426110	47.3	95.23	101.07
1927	369399	46.4	82.56	99.15
1929	447448	46.8	100	100
1931	285515	36.9	63.81	78.85
1933	243614	35.2	54.45	75.21
1935	387801	37.3	86.67	79.7
1937	469170	38.2	104.85	81.57
1939	388097	37.8	86.74	80.82

Sources: Production, Employment and Productivity in 59 Manufacturing Industries, Works Progress Administration, National Research Project; Man-hour Statistics for 171 Selected Industries, Census of Manufactures:1939; Man-hour Statistics for 105 Selected Industries, Census of Manufactures: 1937.

Table 3.30. Total Factor Productivity for *Motor Vehicles* Industry (Annual Wage Rate)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	122.98		106.01		
1921	122.29	124.93	109.38	111.1	
1923	110.77	112.12	100.59	100.46	
1925	106.94	107.8	99.97	99.91	
1927	105.13	105.73	101.8	102.19	
1929	100.00	100.00	100.00	100.00	100.00
1931	100.52	100.21			88.06
1933	99.64	98.52			77.51
1935	92.63	90.88			63.98
1937	88.99	87.08			54.59
1939	87	85.07			48
N	275	250	150	125	150

Table 3.31. Total Factor Productivity for *Motor Vehicles* Industry (Hourly Wage Rate 1)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	121.94		99.16		
1921	120.75	122.55	103.39	105.34	
1923	110.71	112.75	96.62	98.29	
1925	106.88	108.25	97.43	98.57	
1927	104.91	105.61	100.57	101.2	
1929	100.00	100.00	100.00	100.00	100.00
1931	99.92	99.50			86.80
1933	98.36	97.25			74.72
1935	91.79	90.22			61.57
1937	88.39	86.59			52.69
1939	86.37	84.21			45.87
N	275	250	150	125	150

Table 3.32. Total Factor Productivity for *Motor Vehicles* Industry (Hourly Wage Rate 2)

Year	1919-39 Model I	1921-39 Model II	1919-29 Model III	1921-29 Model IV	1929-39 Model V
1919	127.62		102.04		
1921	126.39	130.36	105.64	106.35	
1923	113.19	115.84	98.13	97.75	
1925	108.37	110.07	98.43	98.20	
1927	105.98	107.02	101.06	101.16	
1929	100.00	100.00	100.00	100.00	100.00
1931	100.07	99.93			90.09
1933	98.42	97.75			80.75
1935	90.52	89.05			65.99
1937	86.56	84.81			56.62
1939	84.31	82.29			49.8
N	275	250	150	125	150

Table 3.33. Summary of *Cotton Goods* Industry of the United States

Year	**Mills**	**Total Spindles ('000)**	**Inactive Spindles ('000)**	**Total Looms**	**Cotton Consumed (running bales)**	**Wage Earners**	**Wages Paid ('000)**
1850	1094	3998			577	92236	16275
1880	756	10053		225759	1570	172544	42041
1919	1288	36443		692169	5766	430966	355475
1921	1328	36618	571		4893	412058	328227
1923	1375	37409	1149		6666	471503	396603
1925	1366	37929	2897		6193	445184	353883
1927	1347	36696	2286	715046	7190	467596	380910
1929	1281	34820	2403	653667	7091	424916	324289
1931	1140	32673	3693	588128	5263	329962	219680
1933	1057	30893	3998		6137	379445	216384
1935	1042	30093	3392	509345	5361	369062	236339
1937	1116	26982	1563			432885	321057
1939	1085	26372	1598	442587		395999	280760

Sources: Years 1919-35: Table 4, Wages In Cotton-Goods Manufacturing, Bulletin 663, Bureau of Labor Statistics, November 1938; Year 1937: Census of Manufactures, 1937; Year 1939: Census of Manufactures, 1939.

TABLE 3.34. Value Added, Value of Products, Value Added per Man-Hour and Value Added per Spindle in *Cotton Goods* Industry, 1919-29

Year	**Value Added**	**Value of Products (000)**	**Value Added per Spindle (1929=100)**	**Value Added per Wage Earner (1929=100)**
1919	889797919	2125272	138.13	142.54
1921	546018005	1278221	84.36	91.48
1923	757263730	1901126	114.52	110.88
1925	637310204	1714368	95.06	98.83
1927	687699650	1567401	106.02	101.54
1929	615478122	1524177	100	100
1931	451404397	305792	78.16	94.45
1933	509270201	861170	93.26	92.66
1935	506233599	983572	95.17	94.7
1937	638241119	1297161	133.82	101.79
1939	678520190	1119671	145.56	118.29

Sources: Data on value added, wage earners, and value of products is from Census of Manufactures, 1919-39. Sources of data for spindles are given in Table 2.30.

Table 3.35. Total Factor Productivity for *Cotton Goods* Industry (Annual Wage Rate)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	110.31		106.51		
1921	107.45	106.98	104.57	101.88	
1923	106.97	106.62	105.33	102.1	
1925	103.52	103.22	102.14	99.35	
1927	102.41	102.26	101.74	100.27	
1929	100.00	100.00	100.00	100.00	100.00
1931	99.30	99.57			94.38
1933	99.98	100.49			90.71
1935	98.93	99.67			87.07
1937	99.59	100.62			85.34
1939	99.74	100.99			83.2
N	253	230	138	115	138

Table 3.36. Total Factor Productivity for *Cotton Goods* Industry (Hourly Wage Rate 1)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	110.22		106.4		
1921	107.36	105.45	104.44	101.76	
1923	106.78	105.84	105.09	101.86	
1925	103.35	102.87	101.93	99.14	
1927	102.25	102.02	101.55	100.07	
1929	100.00	100.00	100.00	100.00	100.00
1931	99.63	98.85			94.81
1933	100.90	99.34			91.89
1935	100.33	98.87			88.81
1937	101.27	100.10			87.39
1939	101.70	100.39			85.54
N	253	230	138	115	138

TABLE 3.37. Total Factor Productivity for *Cotton Goods* Industry (Hourly Wage Rate 2)

Year	**1919-39 Model I**	**1921-39 Model II**	**1919-29 Model III**	**1921-29 Model IV**	**1929-39 Model V**
1919	111.46		103.49		
1921	107.85	106.43	102.87	109.55	
1923	107.43	106.39	103.81	106.36	
1925	103.73	103.15	100.98	101.04	
1927	102.48	102.15	101.27	101.2	
1929	100.00	100.00	100.00	100.00	100.00
1931	99.07	99.10			91.91
1933	99.86	99.87			86.64
1935	99.05	99.30			82.10
1937	100.01	100.41			79.5
1939	100.21	100.78			76.56
N	253	230	138	115	138

TABLE 3.38. Estimation Results from Total Factor Productivity Equation for *Motor Vehicles and Parts* Industry

Variable	Estimate	t-ratio	Elasticity	1 Unit Std. Dev.
YEAR19				
YEAR21				
YEAR23	-0.0308***	-2.62	-0.0028	-0.1188
YEAR25	-0.0099***	-4.48	-0.0009	-0.038
YEAR27	-0.0011	-0.66	-0.0001	-0.004
YEAR29	-0.0151***	-3.84	-0.0014	-0.0581
YEAR31	0.0120**	2.42	0.0011	0.0463
YEAR33	0.0158***	2.7	0.0014	0.0608
YEAR35	0.0021	0.82	0.0002	0.0081
YEAR37	0.0032**	1.97	0.0003	0.0123
YEAR39	0.0077**	2.31	0.0007	0.0296
STRIKES	-0.00001**	-3.46	-0.0008	-0.0173
OUTPUT_CHANGE	-0.0700***	-193.09	-0.017	-1.0034
CAPACITY	0.0329***	3.09	0.0287	0.1868
EMPLOYMENT	-0.0181*	-2.17	-0.0003	-0.0101
Constant	-0.0487***			
No. of Observations	275			

Notes: The dependent variable is TFP. This TFP measure is developed from the model with regional effects and hourly wage measure 2. I have excluded years 1919 and 1921 here because the CAPACITY variable becomes collinear with the year indicator as capacity utilization in some years is equal to 1.

TABLE 3.39. Estimation Results from Total Factor Productivity Equation for *Cotton Goods* Industry

Variable	**Estimate**	**t-ratio**	**Elasticity**	**1 Unit Std. Dev.**
YEAR19				
YEAR21	0.0211***	23.08	0.002	0.176
YEAR23	0.0030***	3.25	0.0003	0.025
YEAR25	0.0061***	6.41	0.0005	0.051
YEAR27	0.0137***	14.43	0.0013	0.114
YEAR29	0.0121***	12.82	0.0011	0.101
YEAR31	0.0292***	29.06	0.0027	0.243
YEAR33	0.0293***	26.74	0.0027	0.244
YEAR35	0.0201***	18.48	0.0018	0.168
YEAR37	0.0190***	19.9	0.0017	0.159
YEAR39	0.0261***	27.76	0.0024	0.218
STRIKES	-0.0000**	-2.36	-0.0029	-0.015
$OUTPUT\_CHANGE$	0.0683***	158.05	0.0034	0.96
CAPACITY	-0.0098**	-2.61	-0.009	-0.021
EMPLOYMENT	-0.0004***	-5.62	-0.0008	-0.032
Constant	-0.0208***	-5.47		
No. of Observations	253			

Notes: The dependent variable in this case is the TFP. This TFP measure is developed from the model with regional effects and hourly wage rate measure 2.

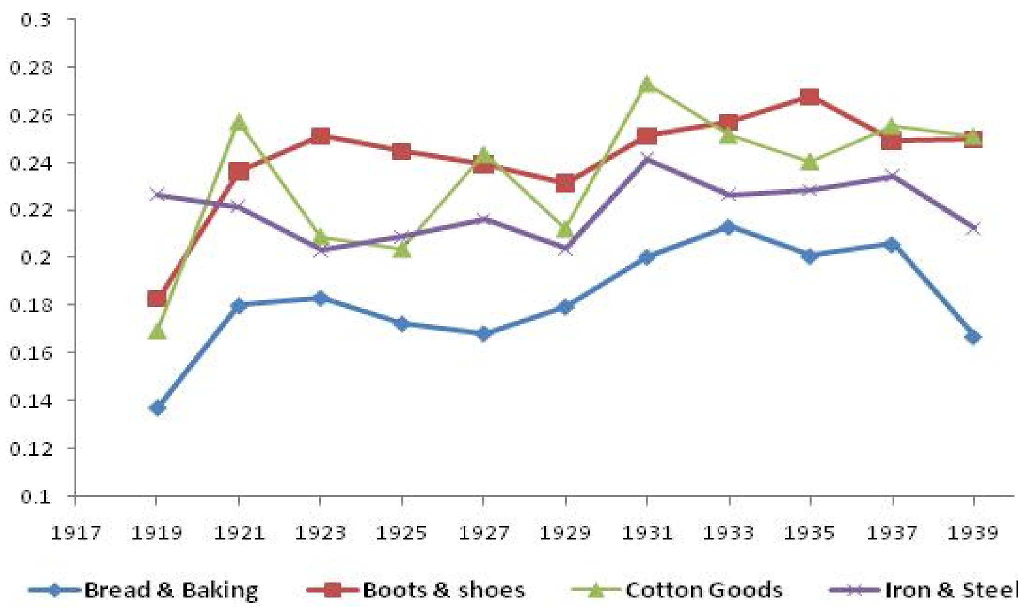

FIGURE 3.1. Share of Wage Labor for Selected Industries, 1919-39

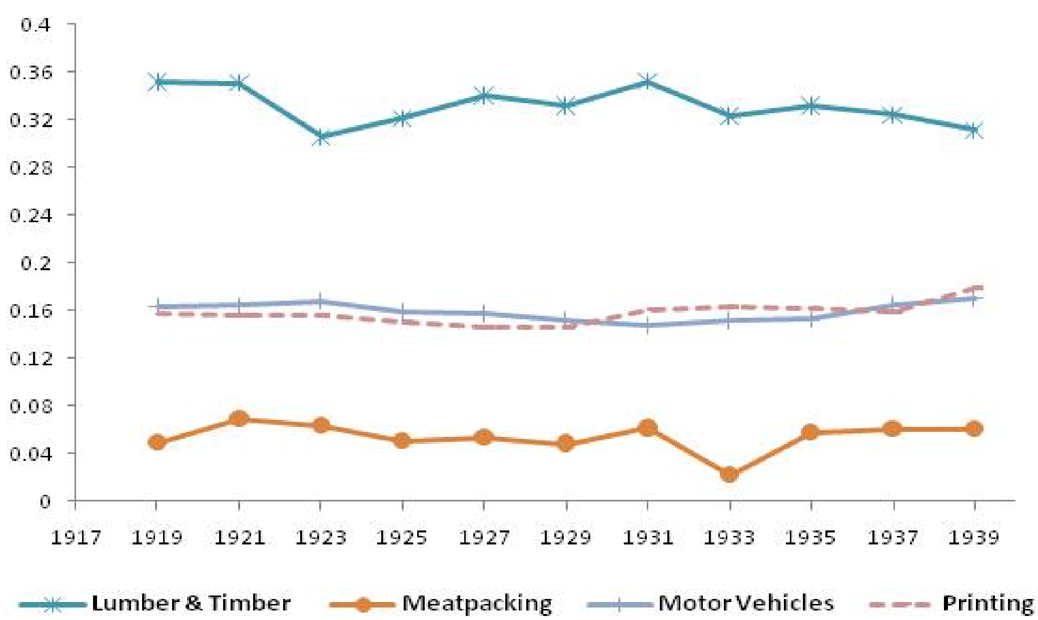

FIGURE 3.2. Share of Wage Labor for Selected Industries, 1919-39

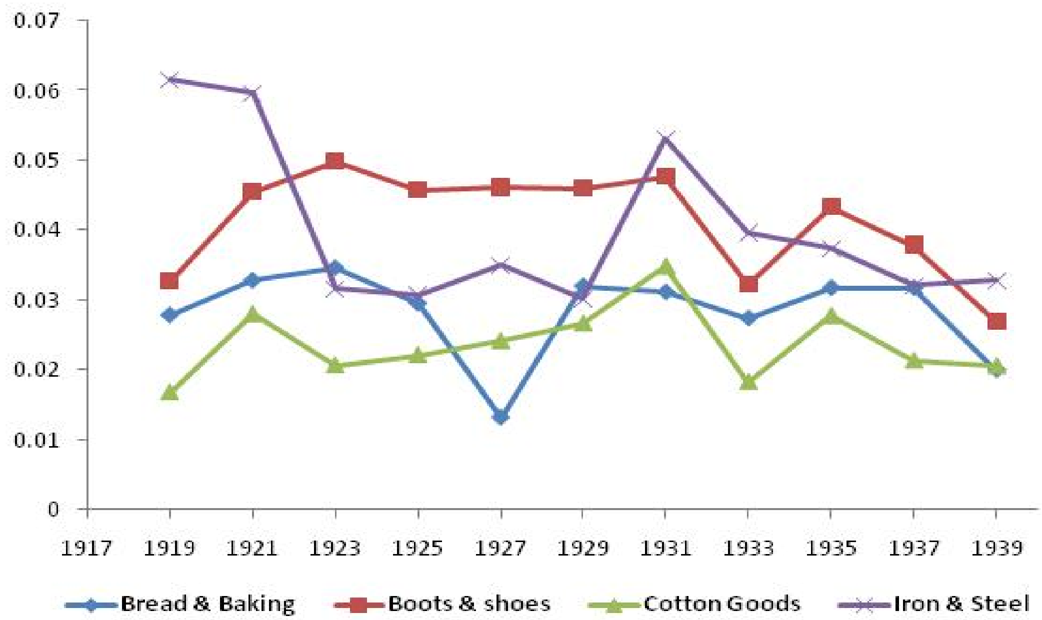

FIGURE 3.3. Share of Salaried Labor for Selected Industries, 1919-39

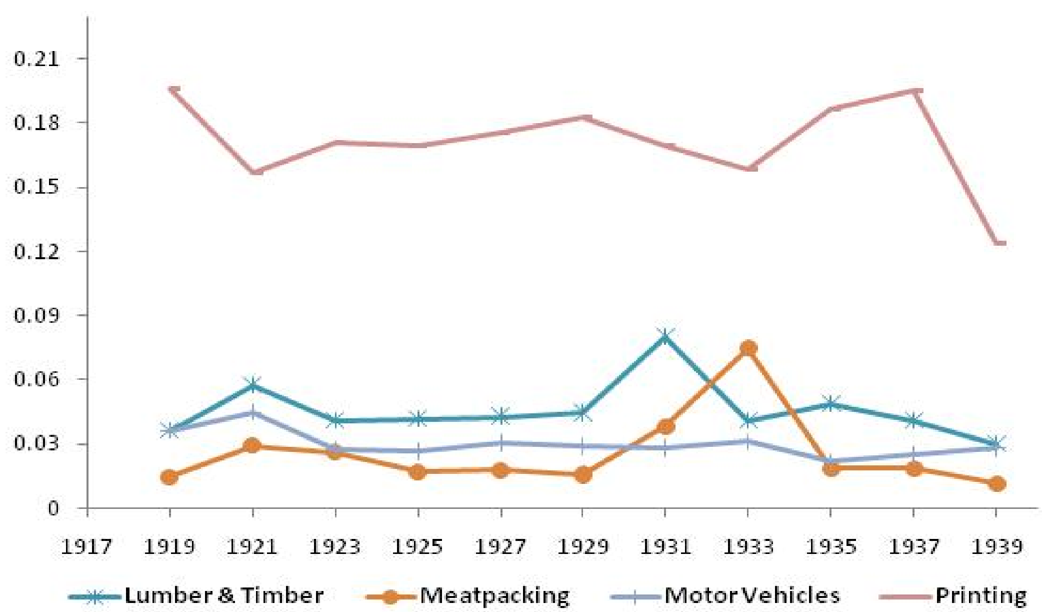

FIGURE 3.4. Share of Salaried Labor for Selected Industries, 1919-39

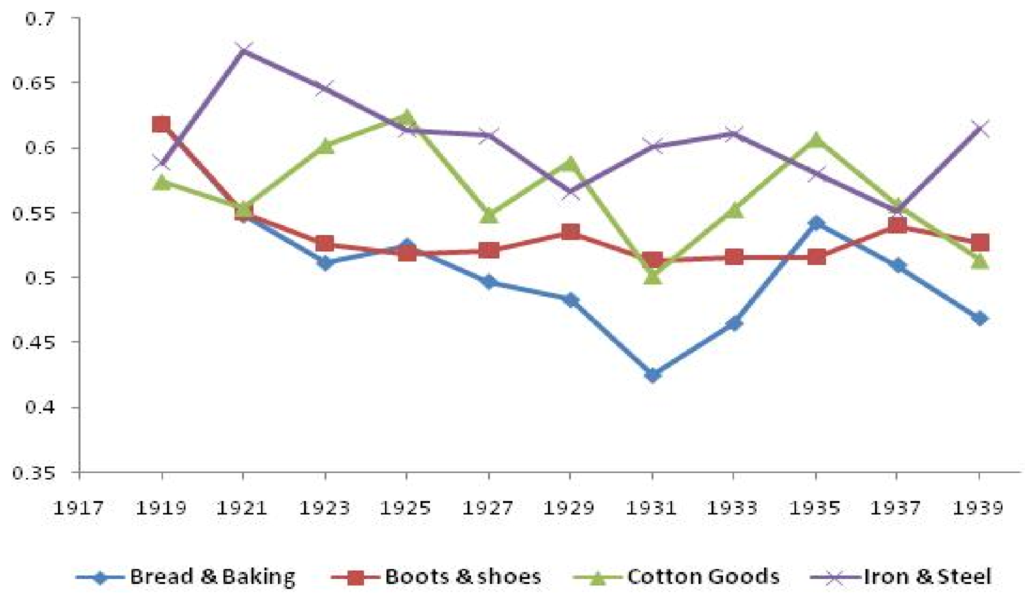

FIGURE 3.5. Share of Materials in Total Cost for Selected Industries, 1919-39

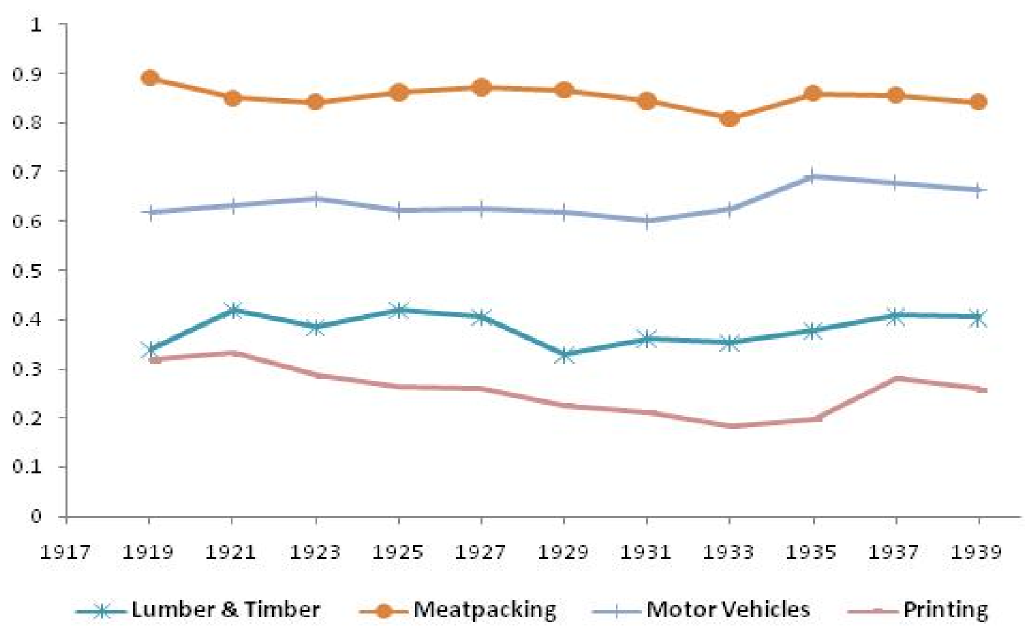

FIGURE 3.6. Share of Materials in Total Cost for Selected Industries, 1919-39

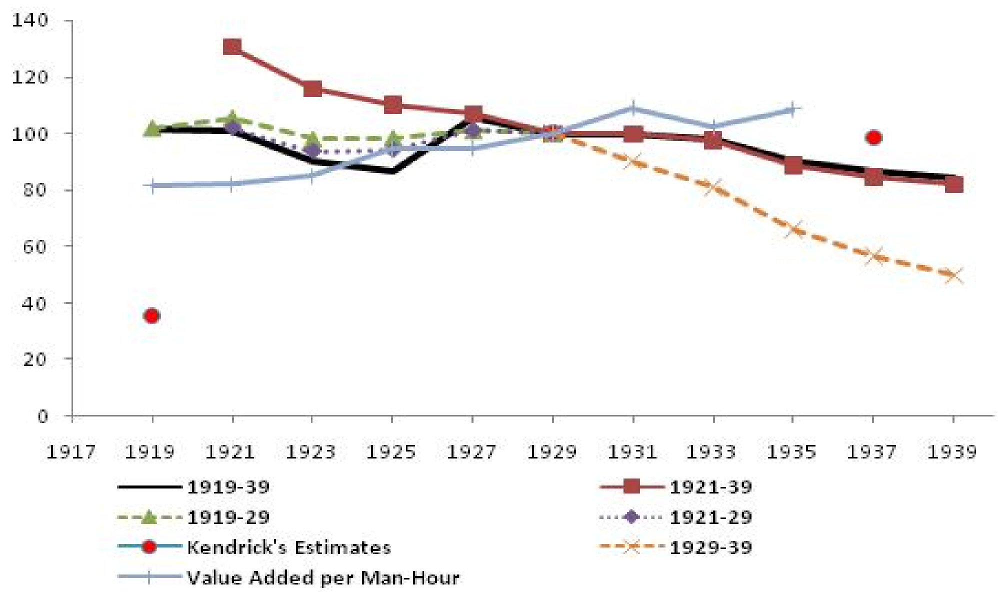

FIGURE 3.7. Total Factor Productivity, Value Added per Man-Hour for *Motor Vehicles* Industry (1929=100)

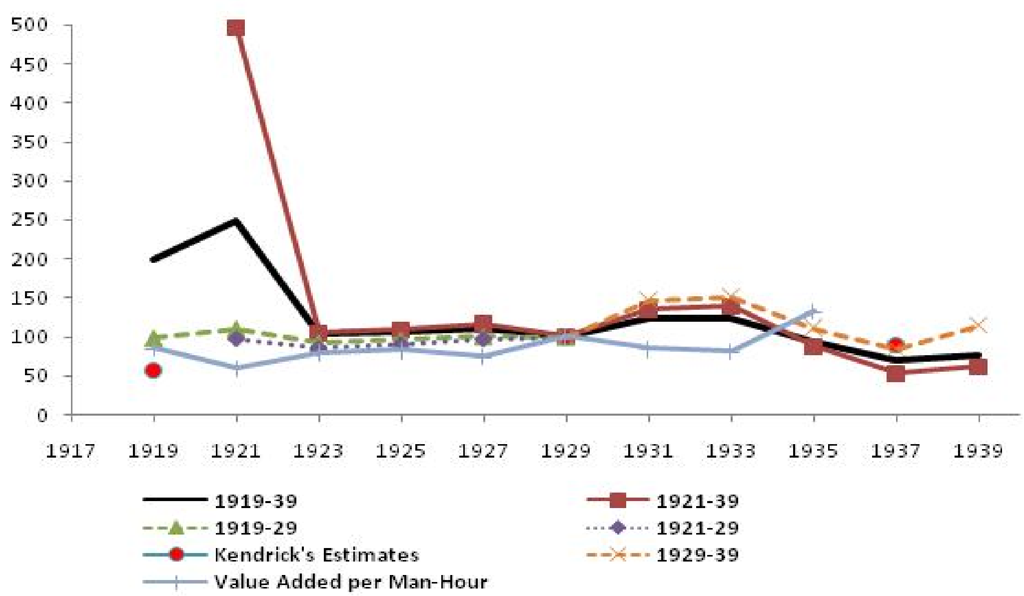

FIGURE 3.8. Total Factor Productivity, Value Added per Man-Hour for *Iron and Steel* Industry (1929=100)

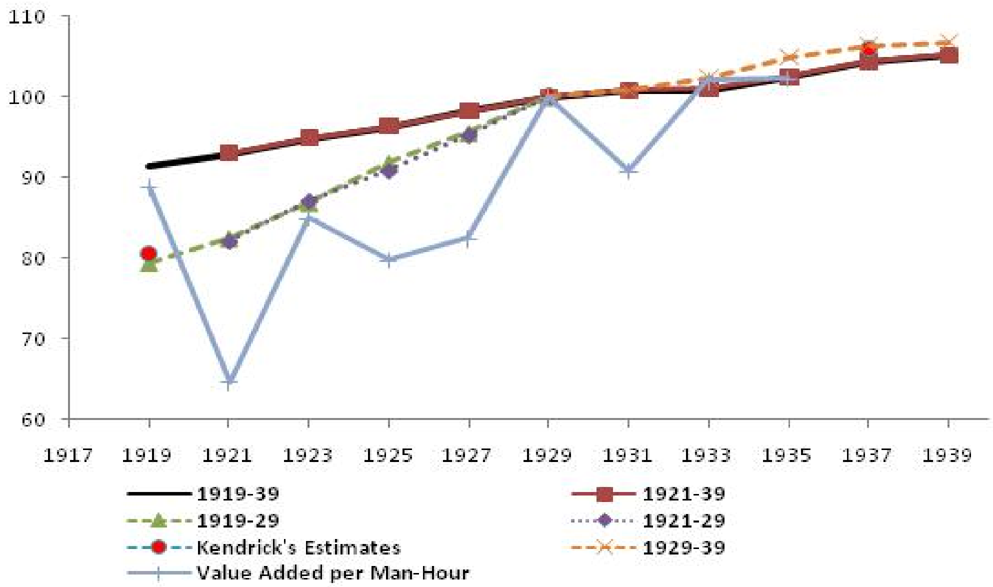

FIGURE 3.9. Total Factor Productivity, Value Added per Man-Hour for *Bread and Other Bakery Products* Industry (1929=100)

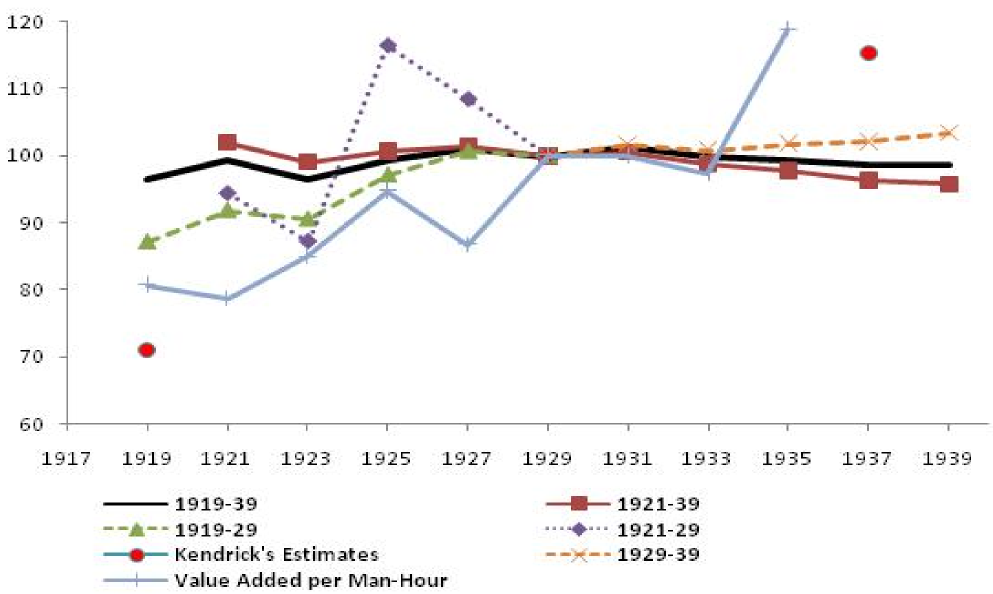

FIGURE 3.10. Total Factor Productivity, Value Added per Man-Hour for *Meatpacking* Industry (1929=100)

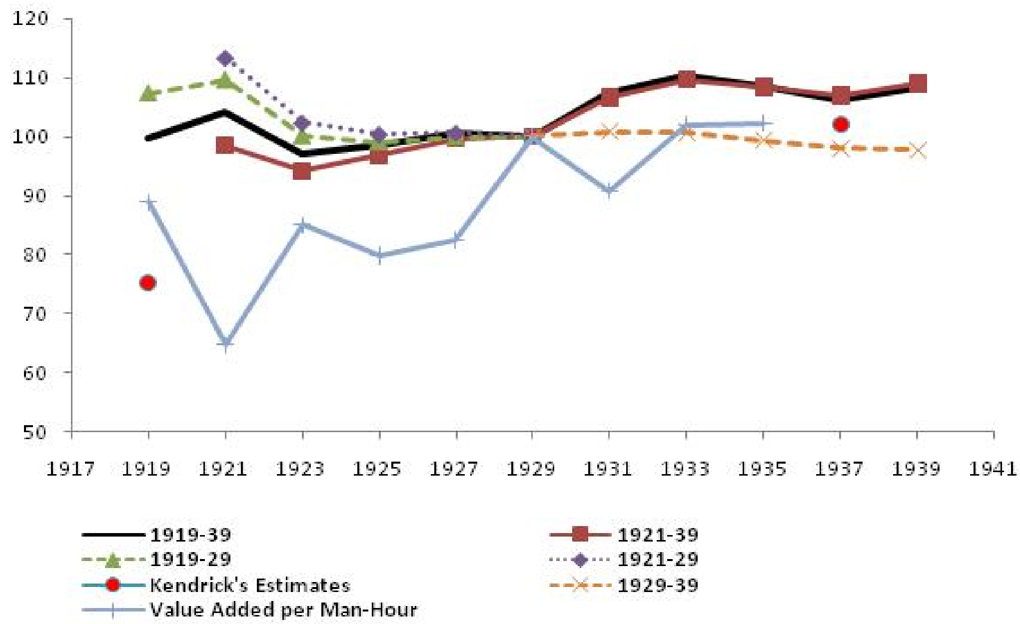

Figure 3.11. Total Factor Productivity, Value Added per Man-Hour for *Lumber and Timber* Industry (1929=100)

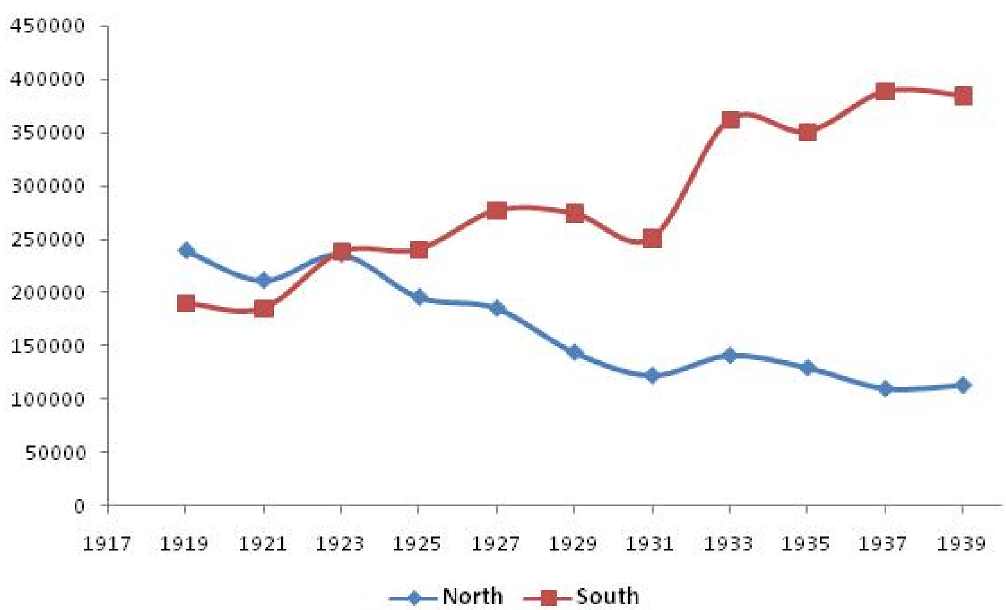

Figure 3.12. Wage Earners for the *Cotton Goods* Industry, 1919-39

Figure 3.13. Value of Products for the *Cotton Goods* Industry, 1919-39

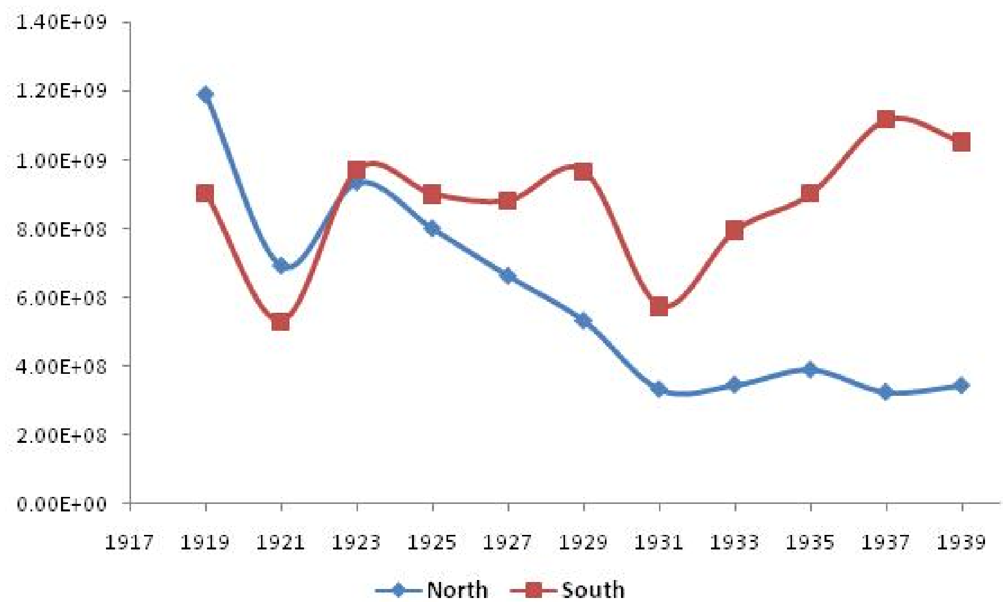

Figure 3.14. Value Added for the *Cotton Goods* Industry, 1919-39

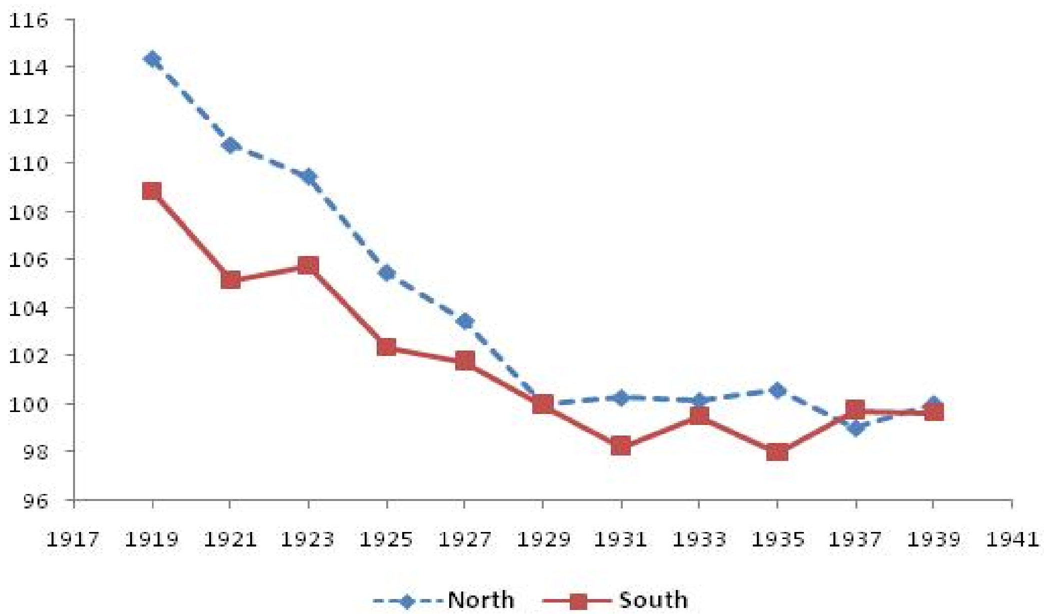

FIGURE 3.15. Total Factor Productivity for the *Cotton Goods* Industry in the North and South

Chapter 4
Conclusion

Past decade has witnessed a surge in activist campaigns that are focused on motivating firms to behave in environmentally responsible ways. Still, the common perception is that activist campaigns have only limited usefulness. The findings reported in chapter two challenge this theory and provide evidence in favor of the importance of activist campaigns in regulating firms' behavior. These campaigns can play an important role in improving environmental performance of the firms. The research in chapter two can be extended in several interesting directions. Focus so far has been to study the relationship between activist campaigns and a firm's environmental performance. It will be interesting to extend this analysis to include government as a player and study the link between private politics and enforcement activity by the government. Activist campaigns can act as compliment or a substitute to the enforcement activity by the government. Estimation of inspection and enforcement equations can help determine if the activist campaigns result in tightening of government regulation. So far, empirical results from chapter two establish that activist campaigns *spur* firms to self regulate. Another avenue to explore is whether a firm can avoid becoming the target of an activist campaign by going green and adopting environment friendly measures. This research could have important consequences for the formulation of environmental policy of firms. In this research, no distinction is made between small and big environmental groups and if there is any difference in their targeting strategy. Also, no research is done on what makes a campaign successful. These are other possible avenues for further research.

The main aim of chapter three is to reconcile the conflicting picture of TFP in

1920s and 1930s and explain how TFP is influenced by the major changes in the economy during the Interwar period from 1919 through 1939. Empirical analysis shows that neither there was large TFP decline during the years 1929-33 in the industries studied, nor was there a sharp increase between 1933 and 1939 in TFP in most of these industries. One possible extension of this work is to perform the same analysis with the firm level data. These estimates would provide a check for the TFP estimates reported in the chapter three and also for TFP estimates reported elsewhere in the literature. This would help to understand the trends in TFP in 1920s and 1930s better. Another possible avenue to extend this work is to categorize the industries based on their structure - competitive, oligopolistic etc. and analyze whether the trends in TFP can be explained by the structure of an industry.

Appendix A

Supplementary Tables for Chapter 2

Table A-1. List of Boycotted Firms by the Type of Boycott

COMPANY NAME	**BOYCOTT TYPE**
American Express	Animal Rights
Anheuser-Busch	Animal Rights
AT&T	Environment Related
Avon Products	Animal Rights
Chevron	Environment Related
Clorox	Environment Related
Coca-cola	Animal Rights
Disney	Environment Related
General Electric	Environment Related
General Motors	Environment Related
Georgia-Pacific	Environment Related
Gillette	Animal Rights
Heinz (H J)	Environment Related
Home Depot	Environment Related
ITT Corporation	Environment Related
McDonald's	Environment Related
Mellon Financial	Animal Rights
Molson Coors Brewing	Animal Rights
Procter & Gamble	Animal Rights
Sysco	Environment Related
Unocal	Environment Related
Weyerhaeuser	Environment Related

Table A-2. Description of Issues for Proxy Votes

Obs. No.	**Issue**
1	Acid rain review committee
2	Report on Comanche Peak nuclear plant
3	Report on Savannah River nuclear plant
4	Report on boiling water reactors
5	Report on nuclear transportation
6	Report on pesticide plant hazards
7	Report on Valdez principles
8	Environmental hazards
9	Reduce CFC use
10	Report on nuclear reactor business
11	Uranium cleanup
12	Report Auto fuel economy
13	Endorse Ceres Principles

Table A-3. Description of SIC Codes

SIC Code	**Industry**
13	Oil and Gas Extraction
20	Food and Kindred Products
26	Paper and Allied Products
27	Commercial Printing
28	Chemicals and Allied Products
29	Petroleum Refining and Related Industries
33	Primary Metal Industries
35	Industrial And Commercial Machinery And Computer Equipment
36	Electronic And Other Electrical Equipment
37	Transportation Equipment
38	Measuring, Analyzing, And Controlling Instruments
48	Communications
49	Electric, Gas, Sanitary Services
60	Depository Institutions
63	Insurance Carriers
73	Business Services

Table A-4: Estimation Results for Boycott Equation: Probit Models

Variable Name	Estimate	Std. Error
NOEMPLOYEES88	0.0002***	0.0001
FINALGOOD (Firm sells final Product)	0.0059	0.0166
RELEMISSIONS89 (CAA emissions relative to industry)	-0.6266	0.8615
CAAEMISSIONS89	0.6277	0.8618
SIERRA88	0.0025	0.0065
STRICT (State has strict liability statute)	-0.0478	0.0387
SPENDAIRQUA (State spending on air quality programs)	0.0085	0.0162
EDUC	-0.0037	0.0074
LAWYERSPERCAP	-0.0099	0.0184
RIGHTTOWORK (State has right to work statute)	0.0296	0.044
AVERAGEINCOME	0.0125	0.0091
SIC28	0.057	0.0513
SIC37	-0.0097	0.0274
Intercept	-3.3778	1.1849
Log-Likelihood	-65.29	

Table A-4: Estimation Results for Boycott Equation: Probit Models

Variable Name	Estimate	Std. Error
Chi-sq	14.84	
(p-value)	(0.3176)	
N	459	

Notes: Dependent Variable for this equation is boycott variable (binary).

The boycotts here are non-environmental and non-animal rights.

We report marginal effects here and standard errors are reported in parenthesis.

Parameter estimate is reported for intercept.

*** significant at 1%, ** significant at 5%, * significant at 10%.

Table A-5. Stability Tests for Random Effects Probit

	Fitted Quadrature (12 points)	**Comparison Quadrature (8 points)**	**Comparison Quadrature (16 points)**
Model I			
Log-Likelihood	-1203.11	-1203.08	-1203.05
Difference		0.03027	0.06030
Relative Difference		-0.00003	-0.00005
Model II			
Log-Likelihood	-1194.59	-1194.55	-1194.51
Difference		0.04321	0.07837
Relative Difference		-0.00004	-0.00007
Model III			
Log-Likelihood	-1142.12	-1142.05	-1142.01
Difference		0.07117	0.11755
Relative Difference		-0.00006	-0.00010

Table A-6: Determinants of Adoption of EMS System: Probit Models

Variable Name	Model I	Model II	Model III
BOYCOTT	0.193	0.329***	0.299**
	(0.122)	(0.113)	(0.105)
PROXYVCS (Cross sectional proxy vote variable)	0.206**	0.250***	0.039
	(0.078)	(0.091)	(0.117)
NOEMPLOYEES89		0.001	0.003**
		(0.001)	(0.001)
FINALGOOD (Firm sells final product)		-0.229**	-0.048
		(0.098)	(0.122)
TOTALASSETS89		-0.007***	-0.010***
		(0.002)	(0.003)
SIERRA89		-0.047*	-0.025
		(0.024)	(0.027)
STRICT (State has strict liability statute)		-0.216**	-0.159
		(0.089)	(0.097)
SPENDAIRQUA (State spending on air quality programs)		0.057	0.067
		(0.051)	(0.057)
EDUC		0.031*	0.026
		(0.018)	(0.021)
LAWYERSPERCAP		-0.207***	-0.134*
		(0.069)	(0.079)
RIGHTTOWORK (State has right to work statute)		-0.183**	-0.095
		(0.077)	(0.095)
SIERRA*FINALGOOD		-0.025	-0.047
		(0.038)	(0.043)
STRICT*NOEMPLOYEES		-0.0002	-0.002
		(0.001)	(0.001)
RELEMISSIONS89 (CAA emissions relative to industry, 1989)			0.0004***
			(0.0001)
CAAEMISSIONS89			-0.0004***
			(0.0001)
EPAINSPECTIONS89			0.009*
			(0.006)
SIC28	0.513***	0.480***	0.400***
	(0.061)	(0.079)	(0.078)
SIC37	0.253**	0.121	-0.049
	(0.098)	(0.116)	(0.153)
SIC38	0.254**	0.093	0.088

Table A-6: Determinants of Adoption of EMS System:
Probit Models

Variable Name	Model I	Model II	Model III
	(0.112)	(0.127)	(0.130)
SIC49	-0.455***	-0.476***	-0.555***
	(0.043)	(0.031)	(0.057)
Intercept	-0.289	0.732	-0.243
	(0.073)	(0.534)	(0.602)
Log-Likelihood	-266.512	-234.77	-191.311
Chi-sq	98.04	161.53	248.45
(p-value)	(0.000)	(0.000)	(0.000)
N	459	459	459

Appendix B

Notes on Hourly Data Construction

We have employed the data from several sources to construct the hourly wage rate data for baking industry. The current data set allows us to calculate only the annual average wage rate. It does not contain the data on hourly wage rate. However, during the depression years, the workers were not working the normal working hours. The annual average wage rate does not take into account reduced work hours. Due to this reason we need to construct hourly wage rate estimates. Listed below are the sources of data for different years:

1. 1919: Labor Statistics Bureau Bulletin 274
2. 1921: Labor Statistics Bureau Bulletin 325
3. 1923: Labor Statistics Bureau Bulletin 354
4. 1925: Labor Statistics Bureau Bulletin 431
5. 1927: Labor Statistics Bureau Bulletin 457
6. 1929: Labor Statistics Bureau Bulletin 540
7. 1931: Labor Statistics Bureau Bulletin 566
8. 1933: Labor Statistics Bureau Bulletin 600
9. 1935: Monthly Labor Review, April 1937, vol. 44, pp. 968
10. 1937: Monthly Labor Review, February 1938, vol 46, pp. 468
11. 1939: Hours and Earnings, volume 673

Creation of a measure of hourly wage rate for each state for years $1919 - 1939$ requires making some simplifying assumptions. The hourly wage data for bakery trades is reported for different occupations : oven men, foremen, mixers, and helpers etc. We need to make a decision regarding which occupation to pick. We have made this decision based on availability of data. We have picked the occupations with the largest number of observations over the years: foremen and oven men. Foremen usually earn the highest hourly wages. However, foremen might fall in the category of salaried workers. We have also constructed hourly wage rate data for oven men for all the states. Oven men fall in the category of wage labor. In our analysis we have used the hourly wage rate for both foremen and oven men. This allows us to compare our estimation results with hourly wage rate for foremen and hourly wage rate for oven men. The coverage on these occupations is not uniform across the cities and not continuous over the years. That is, the data on same occupations is not reported consistently across the cities or over time. The missing data is created by straight line interpolation using the national numbers.

The data on occupations is reported as separate categories for some instances and clubbed together for some other years and some cities. E.g. foremen and oven men are reported as one category for some years. We deal with this problem by comparing the years where the occupations (eg. Oven men and mixers) are reported separately as different categories to the years where they are clubbed together as one category. If the wages are the same in both the cases, then we assume that oven men and mixers have the same wages. However, if they do not have same wages, then we take an average over both the categories. This will give us the hourly wage rate for an average foremen or oven men.

The data is divided in terms of: hand and machine bakeries, night work and day work, Hebrew, polish, Scandinavian and ordinary bakeries. In the earlier years the data on the bakeries is reported for both hand and machine bakeries. In the later years sometimes that data is reported for both the hand and machine bakeries but in some years this distinction is not made. We have made the assumption that over the years more and more bakeries will be mechanized. In the later years, if it is not clear if we are dealing with hand or machine bakeries, we have made the assumption that the data reported is for machine bakeries. Likewise, for the cities reporting data on both hand and machine bakeries, we have concluded that the data is from machine bakeries. This assumption is supported by the information provided by the Labor Statistics Bureau bulletin. According to this volume bread baking industry was affected by rapid process in the displacement of hand processes by machine operations in 1900s. Census of Manufactures reports that the percentage of bakeries reported the use of power was 5.3 in 1889, 9.8 in 1899, 25.9 in 1909, and 68.3 in 1919. These figures indicate considerable acceleration in mechanization.

The hourly wage rates also vary by daytime and night time. Night time wages tend to be higher than day time wages. We are reporting the day time wages. The bakeries are categorized into: Hebrew, polish, ordinary and Scandinavian bakeries. The data for special bakeries like Hebrew, polish etc is available for some years and some cities. Hourly wages paid by Hebrew bakeries were higher than those paid by other bakeries and their working hours were longer. We have used the data from ordinary bakeries.

In some cases, wages are reported for foremen based on their numbers. eg. wages if foremen and 2 or less men work in the bakery, or wages if foremen, and 5 to 8 men work in the bakery. These wages differ from each other. In these cases we take an average and we get hourly wage rate for an average foremen.

The hourly wages are reported only for specific cities. These cities do not cover all the 48 states. This problem is dealt with by assigning the state with no information the hourly wages of the closest neighboring state. We have also experimented with assigning the average of the hourly wages of all the neighboring states. However, some of the states are surrounded with states that do not have data on hourly wages e.g. Florida. There is no data on the hourly wage rates of any of the states surrounding Florida. We imputed hourly wage rate for the states with no data using the data of neighboring states. This allowed us to impute hourly wage rates for the states like Florida as well. This involves taking the average twice but given the data limitations, it seems reasonable to do. Table A1 shows the states for which hourly wage information is available and the states for which hourly wage rate is an average of the imputed hourly wages of the neighboring states.

For some states, we have information on more than one city. If we have information on more than one city, we need to choose one city. If we have information for all the years for both the cities, then we pick the city that has larger number of wage earners. If we have more information on the smaller city then we pick the smaller city. However, most of the states have information on only one city. In this case the missing values are filled by straight line interpolation. We dealt with the problem of missing values for the year 1919 by extrapolating for year 1919.

Table B-1: Information on Calculation of Hourly Wages for Foremen

State Name	**Sources of Hourly Wages Data**
Alabama	Same as that of Louisiana
Arizona	Same as that of California
Arkansas	Same as that of Louisiana
California	Based on information from BLS volumes
Colorado	Based on information from BLS volumes
Connecticut	Based on information from BLS volumes
Delaware	Average of the hourly wages in Pennsylvania and New Jersey
Florida	Average of the hourly wages in Alabama, and Georgia
Georgia	Average of the hourly wages in Alabama and Tennessee
Idaho	Average of the hourly wages in Montana, Washington and Oregon
Illinois	Based on information from BLS volumes
Iowa	Average of the hourly wages in Missouri, Illinois, Wisconsin and Minnesota
Indiana	Based on information from BLS volumes
Kansas	Average of the hourly wages in Colorado and Missouri
Kentucky	Based on information from BLS volumes
Louisiana	Based on information from BLS volumes
Maine	Same as that of New Hampshire
Maryland	Same as that of Pennsylvania
Massachusetts	Based on information from BLS volumes
Michigan	Average of the hourly wages in Ohio and Indiana
Minnesota	Based on information from BLS volumes
Mississippi	Same as that of Louisiana
Missouri	Based on information from BLS volumes
Montana	Based on information from BLS volumes
Nebraska	Same as that of Colorado
Nevada	Average of the hourly wages in Oregon and California
New Hampshire	Based on information from BLS volumes
New Jersey	Based on information from BLS volumes
New Mexico	Average of the hourly wages in Texas and Colorado
New York	Based on information from BLS volumes
North Carolina	Average of the hourly wages in Virginia and Tennessee
North Dakota	Average of the hourly wages in Minneapolis and Montana

Table B-1: Information on Calculation of Hourly Wages for Foremen

State Name	**Sources of Hourly Wages Data**
Ohio	Based on information from BLS volumes
Oklahoma	Average of the hourly wages in Colorado, Missouri and Texas
Oregon	Based on information from BLS volumes
Pennsylvania	Based on information from BLS volumes
Rhode Island	Based on information from BLS volumes
South Carolina	Average of the hourly wages in Kentucky and Tennessee
South Dakota	Average of the hourly wages in Minneapolis and Montana
Tennessee	Average of the hourly wages in Missouri, Kentucky and Virginia
Texas	Based on information from BLS volumes
Utah	Same as that of Colorado
Vermont	Average of the hourly wages in New York, New Hampshire and Massachusetts
Virginia	Same as that of Kentucky
Washington	Based on information from BLS volumes
West Virginia	Average of the hourly wages in Ohio, Kentucky and Pennsylvania
Wisconsin	Based on information from BLS volumes
Wyoming	Average of the hourly wages in Colorado and Montana

The data on oven men is much more limited than the data on wages of foremen. Sometimes wages for oven men and mixers are reported as one category and sometimes these wages are reported as two separate categories - oven men and mixers. Usually, oven men earn less than mixers but there is no definite pattern. If wages for mixers and oven men are reported as one category, then we have assumed that oven men and mixers earn the same wages. This procedure gives us a longer series for oven men. Table A2 shows how the wages for each state are calculated.

Table B-2: Information on Calculation of Hourly Wages for Ovenmen

State Name	**Sources of Hourly Wages Data**
Arizona	Average of hourly wage in California and Utah
Alabama	Same as that of neighboring state Louisiana
Arkansas	Average of the hourly wage in Louisiana
California	Based on information from BLS volumes
Colorado	Based on information from BLS volumes
Connecticut	Based on information from BLS volumes
Delaware	Average of the hourly wage in Pennsylvania and New Jersey
Florida	Average of the hourly wage in Alabama, and Georgia
Georgia	Average of the hourly wage in Alabama and Tennessee
Idaho	Average of the hourly wage in Utah, Washington and Oregon
Illinois	Based on information from BLS volumes
Indiana	Based on information from BLS volumes
Iowa	Average of the hourly wage in Missouri, Illinois, Wisconsin and Minnesota
Kansas	Average of the hourly wage in Colorado and Missouri
Kentucky	Based on information from BLS volumes
Louisiana	Based on information from BLS volumes
Maine	Same as that of neighboring state New Hampshire
Maryland	Average of the hourly wage in Pennsylvania
Massachusetts	Based on information from BLS volumes
Michigan	Based on information from BLS volumes
Minnesota	Based on information from BLS volumes
Mississippi	Same as that of neighboring state Louisiana
Missouri	Based on information from BLS volumes
Montana	Based on information from BLS volumes
Nebraska	Same as that of neighboring state Colorado
Nevada	Average of the hourly wage in Oregon and California
New Hampshire	Average of the hourly wage in Vermont
New Jersey	Based on information from BLS volumes
New Mexico	Average of the hourly wage in Texas and Colorado
New York	Based on information from BLS volumes
North Carolina	Average of the hourly wage in Tennessee
North Dakota	Average of the hourly wage in Minneapolis
Ohio	Based on information from BLS volumes
Oklahoma	Average of the hourly wage in Colorado, Missouri and Texas
Oregon	Based on information from BLS volumes
Pennsylvania	Based on information from BLS volumes

Table B-2: Information on Calculation of Hourly Wages for Ovenmen

State Name	**Sources of Hourly Wages Data**
Rhode Island	Average of the hourly wage in Connecticut
South Carolina	Average of the hourly wage in Georgia
South Dakota	Average of the hourly wage in Kentucky, Virginia and Missouri
Texas	Based on information from BLS volumes
Tennessee	Average of the hourly wage in Missouri, Kentucky and Virginia
Utah	Same as that of neighboring state Colorado
Virginia	Same as that of neighboring state Kentucky
Vermont	Average of the hourly wage in New York and Massachusetts
West Virginia	Average of the hourly wage in Ohio, Kentucky and Pennsylvania
Wyoming	Average of the hourly wage in Colorado and Utah
Washington	Based on information from BLS volumes
Wisconsin	Based on information from BLS volumes

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