Essays in Public Finance

by

Jeffrey S. Hicks

M.A., Queen's University, 2015
B.A., Mount Allison University, 2014
Dipl., Algonquin College, 2010

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

in

The Faculty of Graduate and Postdoctoral Studies

(Economics)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

October 2021

The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the dissertation titled “Essays in Public Finance" submitted by Jeffrey Hicks in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics.

Examining Committee:

Kevin Milligan, Professor, Vancouver School of Economics, UBC

Supervisor

Wei Cui, Professor, Peter A. Allard School of Law, UBC

Committee Member

Nicole Fortin, Professor,Vancouver School of Economics, UBC

University Examiner

Hernán Ortiz-Molina, Associate Professor of Finance, Sauder School of Business, UBC

University Examiner

Trevor Tombe, Professor, Department of Economics, University of Calgary

---

External Examiner

Additional Supervisory Committee Members:

Joshua Gottlieb, Associate Professor, Harris School of Public Policy, University of Chicago

---

Co-Supervisor

David Green, Professor, Vancouver School of Economics, UBC

Supervisory Committee Member

Abstract

Each chapter of this thesis investigates one aspect of China's taxation system. **Chapter 1** investigates the introduction of accelerated depreciation (AD) for fixed assets investment in China as a natural experiment. In contrast to the large positive impact of similar tax incentives in the U.S. and U.K. found in recent studies, we document that AD was ineffective in stimulating Chinese firms' investment and that firms fail to claim AD on over 80% of eligible investments. We investigate information frictions as the primary driver of both facts.

Chapter 2 documents new facts about the structure and drivers of China's SI contributory base, with an emphasis on non-compliance. First, 54% of firms do not pay into the employer-based SI system leaving 35% of employees outside of SI coverage. Among participating firms, an estimated 85% of firms are not fully compliant. Second, compliance increases sharply with firm size. Third, China is unique in that SI administration and insurance pooling are done at sub-provincial levels. We investigate how this decentralization contributes to firm non-compliance. **Chapter 3** applies the lessons from **Chapter 2** to analyze China's primary fiscal response to the Covid-19 crisis: an exemption for firms from making SI contributions, resulting in an average tax cut of 21 percentage points on employment. Labor informality substantially reduces the reach of this fiscal response and skews the tax savings towards large firms. Offsetting this negative targeting is the much higher labor intensity of the firms most vulnerable and exposed to the economic shock, which creates a larger benefit from payroll tax cuts for these firms.

Chapter 4 studies the transition from a turnover tax (TT) to a value-added tax (VAT). This reform, the largest Chinese tax reform in a quarter-century, mostly eliminated the taxation of firm inputs. We assess the effects on production, investment, and outsourcing. We find minimal effects on firm output but large increases in fixed asset investment. The latter is driven by an effective 17 percentage point reduction in the tax rate on fixed asset purchases. We also find mixed evidence on whether outsourcing increased due to the reform.

Lay Summary

In just a couple decades, China's ratio of tax revenues to GDP has risen from 10% to 25%. It now collects more tax revenue in dollar terms than any other country on the planet with the exception of the United States. Yet, despite its growth and scale, the study of Chinese taxation is nascent relative to our understanding of tax systems in western countries. In this thesis, I explore the three largest components of this system: the corporate income tax (CIT), social insurance (SI) payroll taxes, and value-added taxes (VAT).

Preface

The research in Chapter 1 is co-authored with Wei Cui and Jing Xing. The research in Chapters 2 and 3 are co-authored with Wei Cui and Max Norton. The research in Chapter 4 is co-authored with Wei Cui and Terry Moon. Outlined below are Jeffrey Hicks' contributions to each.

Jeffrey Hicks was a primary and integral driver of all four projects, beginning with the idea origination and the intellectual development. Wei Cui originated the broad research agenda of studying tax design and administration in China due in part to his gaining access to the novel data set of tax records and financial statements used in all four chapters. Upon joining this agenda, Jeffrey Hicks initiated each of the four specific chapters in this thesis, and was a primary driver of their development and execution: from designing appropriate empirical methods, problem-solving and hypothesis generation, and writing of the results.

Jeffrey did the majority of the data analysis. Wei Cui was crucial in understanding the data, which had not previously been used for research purposes. Jing Xing and Terry Moon also made meaningful data analysis to contributions to Chapters 1 and 4, respectively. Jing Xing collected data on tax administrator resources and accounting resources which were crucial to our analysis in Chapter 1. The analysis of input-output tables in Chapter 4 was executed by Jeffrey and Wei Cui. Max Norton made substantially contributions to the execution of Chapters 2 and 3 – taking part in analysis of the tax return data, working with Wei Cui to clean external budgetary data on SI contributions and collecting other data from Census records.

All four Chapters were written collaboratively. Most notably, Jing Xing and Wei Cui made substantial writing contributions in Chapter 1. Max Norton joined the writing of Chapters 2 and 3, and Terry Moon in Chapter 4. Notwithstanding, Jeffrey Hicks has sole-responsibility for the writing and compilation of this thesis. Chapter 1 has been requested for re-submission at a journal. None of the projects required ethics review.

Table of Contents

List of Tables

List of Figures

Acknowledgements

The research in this thesis was supported by funding from (i) the Social Sciences and Humanities Research Council of Canada through a Doctoral Fellowship Award and (ii) the UBC Public Scholars Initiative.

My committee members all deserve extraordinary recognition for their invaluable guidance during the writing of this dissertation. Their calm and persistent support has exceeded all expectations. I am deeply grateful. In alphabetical order, they are: Wei Cui, Joshua Gottlieb, David Green, and Kevin Milligan.

I am also indebted to Hugh Shiplett. I have had the remarkable privilege of unfettered access to his criminally under-recognized intellect for almost a decade. In his patience and humility, he has never turned me away when I am struggling with a challenging problem. Without him, I would not have succeeded past the first year of the PhD. Thank you, friend.

And of course, most of all, Zuza. How fortunate I am.

Chapter 1

Introduction

By 2019, China's ratio of tax revenues to GDP rose to 25%, roughly the same amount as the United States (U.S). It now collects more revenue in dollar terms than any other country with the exception of the U.S. In contrast to most western countries, however, China raised that revenue in fundamentally different ways. The biggest source of tax revenue was the Value-Added Tax (VAT) (40%), followed by social insurance (SI) payroll taxes (27%), and corporate income tax (CIT) (17%). Only 7% of tax revenue originated from the personal income tax (PIT), a striking contrast to most western nations where the PIT dominates.

Beyond the tax mix, China also differs dramatically in its tax administration apparatus. In contrast to a country like Canada that relies on self-assessment and norms of truthfulness, backed by a centralized tax administration that seeks out violations of those norms, China has a highly decentralized tax administration that in some ways promotes imperfect compliance and eschews self-assessment.

Despite its scale and uniqueness, the study of Chinese taxation is nascent relative to our understanding of tax systems in western countries. This thesis fills the gap. Each chapter investigates one of the three largest tax levers: CIT, SI, and VAT. Chapters 1 and 2 emphasize the role of localized tax administration in both educating taxpayers and shaping (non-)compliance with tax law. A full discussion of relevant literature on each topic is deferred to each individual chapter.

The foundation of all four chapters is proprietary de-identified tax returns and financial statements of firms in a large prosperous province, spanning the period 2010 to 2016. Chapter 1 exploits this data advancement to investigate the introduction of a major investment tax incentive in the CIT. Chapters 2 and 3 leverage it to study the structure of the SI contribution base. Chapter 4 studies China's flagship VAT reform.

Chapter 2

Imperfect Take-up of Tax Incentives and Firm Investment Behavior

Tax incentives for investment are widely used around the world today. They have enjoyed a particularly long history in developed countries. The U.S., for example, introduced accelerated depreciation (AD) in 1954 and investment tax credits in 1962 [Auerbach, 1982]. Yet studies have only recently offered convincing evidence for positive investment responses to such policies [House and Shapiro, 2008; Maffini et al., 2019; Ohrn, 2018; Zwick and Mahon, 2017].[1] Meanwhile, evidence persists that substantial frictions may dampen policy effectiveness. In the U.S., 40-60% of firms did not claim bonus depreciation on eligible investments [Kitchen and Knittel, 2016]. Sources of friction recently examined include losses [Edgerton, 2010], accounting rules that counteract tax rules [Edgerton, 2012; Graham et al., 2017], and compliance costs [Kitchen and Knittel, 2016]. Such frictions continue to fuel critiques of AD and similar policies [Bazel and Mintz, 2019].

This paper analyzes AD's recent introduction in China. China has seen more capital investment than any other country in the last decade [Chen et al., 2019]. Until recently, Chinese tax policy had generally relied on lower tax rates to encourage investment. Facing declining investments and budgetary concerns, the government introduced AD in 2014 as a potentially better-targeted tool. The AD rules were more generous for a subset of industries, delivering benefits comparable to that of U.S. bonus depreciation or U.K. first-year capital allowances. We apply a difference-in-differences (DiD) approach to a data set of confidential corporate tax returns from a large province to study the causal effect of AD on investment. We find that Chinese firms showed limited investment response, in contrast to large responses in the U.S. and the U.K.

Relying on unique features of the tax return data, we uncover one fact that may underlie AD's failure to stimulate investment: firms failed to claim AD on over 80% of eligible investment. We evaluate two complementary explanations for why firms forgo the tax benefits. One is that widespread losses reduce the value of AD. While we find significant disincentive effects of tax losses on claiming AD, even after accounting for this, the take-up rate of AD remains dismal. The second explanation is that, due to poor policy publicity and a lack of prior exposure, many firms are unaware or fail to grasp the policy's benefits. Consistent with this idea, larger firms and those with

[1] Hassett and Hubbard [2002] noted that even in the early 1990s, "almost no economist believed that the investment demand elasticity was much different from zero".

more tax expertise were more likely to claim AD.

This raises the question of whether better information transmission can improve take-up. In China, taxpayers rely heavily on tax administrators for knowledge about tax policy [Cui, 2015]. Each firm is assigned to a local tax bureau responsible for securing compliance and educating taxpayers. Consistent with the hypothesis that resource-constrained tax bureaus will devote less time to taxpayer education, we find that administrators' workload negatively predicts take-up. Firms further away from their tax bureau are also less likely to claim AD, suggesting that tax administrators are better able to convey policies to nearby firms. A series of robustness checks, placebo tests, and heterogeneity results reinforce our interpretation of the effects as the consequence of information transmission from tax administrators to firms.

Finally, we test whether better-informed firms increased investment because of AD, or simply claimed advantageous deductions *ex post*. We find that the largest 5% of firms both are more likely to claim AD than the rest of the sample and displayed a significant investment response. However, in the rest of the sample, proxies for awareness do not predict greater responsiveness. The ineffectiveness of China's AD policy for the large segment of small and medium-sized firms may thus be over-determined: other factors may also have held back investment. While taxpayer understanding of an incentive is not a sufficient condition for it to influence behavior, it is a necessary condition, and we show that even the satisfaction of this basic condition cannot be assumed.

Our study relates to several strands of literature. First, we offer new evidence for the phenomenon of imperfect take-up of tax benefits and explore its causes. Imperfect take-up of AD benefits received frequent comment in the U.S. until the 1980s [Wales, 1966; Auerbach, 1982]. It was also persistent in other corporate tax systems [Kanniainen and Sodersten, 1994] where its causes were not well-understood [Aarbu and Mackie-Mason, 2003; Forsling, 1998; Gronberg, 2015]. In implementing similar incentives in emerging economies, it is unsurprising that similar puzzles of non-responsiveness should resurface. Second, we contribute to the literature on the role of tax administration in policy implementation [Dabla-Norris et al., 2019; Goodspeed et al., 2013]. In contrast to the prior literature's emphasis on the effect of tax administration on tax evasion, we find that tax administration resources can also increase firm engagement with new policies. Our study thus adds to the discussion of information transmission and expertise in tax policy implementation [Abeler and Jäger, 2015; Chetty et al., 2013; Graham et al., 2017]. Finally, we contribute to studies of investment incentives in developing countries [Chen et al., 2019].

Concurrent work by Fan and Liu [2020] also examines AD's introduction in China. They find modestly larger investment effects than our study, but their estimates are still smaller than recent estimates from developed countries. Our study differs from theirs in several significant ways. First and most important, they use a nationwide taxpayer survey and do not observe claimed AD deductions. In comparison, we draw on actual corporate tax returns from one large province, and are able to document low take-up and analyze its drivers. Second, Fan and Liu [2020] use data ending in 2015. As a result, they study only firms eligible for the 2014 AD policy and estimate treatment effects using a single post-treatment year. Our tax return data ends in 2016, which allows us to study both the 2014 and 2015 cohorts of firms eligible for AD—the latter encompasses substantially more firms. Third, their sample consists of mostly large firms, while our sample covers a wide range of the firm size distribution. Fourth, they explore taxpayer non-compliance as an explanation of the muted investment response. We view this as complementary to our analysis, and provide evidence that the effect of information frictions is independent of non-compliance.

The paper proceeds as follows. Section 2.1 provides background on China's adoption of AD and compares the policy to investment incentives studied in recent scholarship. Section 5.2 describes our data. Section 2.3 analyzes firms' investment responses and Section 2.4 documents firms' take-up of AD. Section 2.5 investigates what factors influence take-up of AD and whether firms aware of the policy increased investment. Section 6 concludes by discussing the policy implications of our findings.

2.1 Accelerated Depreciation: Policy Background

AD is a familiar tax policy tool in developed countries. Section 179 expensing and bonus depreciation studied in the recent U.S. literature [Kitchen and Knittel, 2016; Zwick and Mahon, 2017] are only the latest episodes in a long history of similar incentives.[2] In contrast, AD is a new policy instrument in Chinese taxation. The basic depreciation rules in the 2008 Enterprise Income Tax Law (EITL) are extremely simple and provide only for straight-line depreciation and five fixed asset classes, with asset lives ranging from 3 to 20 years.[3] Before the 2014 policy change, AD was permitted only to correct serious errors in the classification of assets for economic depreciation.[4] Moreover, claims were subject to scrutiny by tax administrators and supposed to be verified by field audits. In fact, before 2014 there was no entry for claiming AD separately from regular depreciation on schedule A105080 of the corporate income tax return, where firms report depreciation and amortization deductions.

The Ministry of Finance announced the new AD policy on September 24, 2014, and the State Administration of Taxation issued more detailed rules in October and November 2014. Table 2.1 illustrates the matrix of policies. Effective from January 1, 2014, all firms regardless of industry could immediately expense newly purchased fixed assets with unit value under 5,000 CNY, and

[2]The U.S. first introduced AD in 1954 by allowing taxpayers to use the double declining balance (DDB) and the sum-of-the-year's-digits (SYD) methods, and Section 179 expensing (the most accelerated form of depreciation) became available to small businesses in 1958 [Guenther, 2018]. As uniform depreciation schedules were introduced in the 1960s and 1970s, options for choosing shorter useful lives were also offered [Auerbach, 1982]. This culminated in the Accelerated Cost Recovery System in 1981. Many other industrialized countries have likewise long used AD as a policy tool [Forsling, 1998].

[3]Unlike the tax depreciation rules, Chinese accounting rules allow DDB and SYD depreciation.

[4]In 2012, firms in software development and integrated circuits industries were permitted to access AD, but these firms were relatively few.

newly purchased instruments and machinery with unit value under 1 million CNY used exclusively for R&D.[5] For purchases with unit values greater than 1 million CNY and used exclusively for R&D, firms could also claim AD. A subset of industries were eligible for even more generous AD. Starting from January 1, 2014, firms in six industries could elect to depreciate any newly purchased fixed assets over 60% of the normal asset life (or, alternatively, use the DDB or SYD method), regardless of the size and purpose of the investment.[6] Moreover, Small and Micro Profit Enterprises (SMPEs)[7] in the six industries could immediately expense investments on instruments and machinery partially used for R&D and with unit values under 1 million CNY. In September 2015, these incentives were extended to four additional industries for asset purchases made on or after January 1st, 2015. All AD policies announced in 2014 and 2015 were introduced as permanent measures and they remain in force as of 2021.[8]

As shown in Table 2.1, the preferential AD policies targeted primarily certain manufacturing industries. As these AD incentives were not limited in types of fixed assets, they were more generous than those available to other industries.

Figure A.1 in the Online Appendix plots the search intensity index for the phrase "accelerated depreciation for fixed assets investment" (in Chinese) from the search engine Baidu during the period 2014/01-2016/12. There is a clear jump in search intensity in the week of the 2014 policy announcement, and very little search activity before, indicating that the 2014 policy was likely unexpected. We plot the search intensity index for the phrase "tax reporting" (in Chinese) during the same period for comparison. The two indices co-move, suggesting that search for AD information coincides with return filing.

China's AD policy announced in 2014 and 2015 resembles earlier U.S. policies, such as the shortening of statutory asset lives under the Accelerated Cost Recovery System (ACRS) in 1981[9] and the Modified ACRS (MACRS) in place since 1986. The benefit of AD policy in China is close to that available under MACRS, which permits DDB depreciation.[10] Panel A of Table 2.2 separately calculates the present value (PV) of depreciation deductions under the regular schedule, under AD using 60% asset life, and under DDB (the rough equivalent of MACRS). Denoting $Z_{t,k}$ as the depreciation deduction in year t, the deductions' PV is:

[5] 1 CNY = 0.16 USD during this period.

[6] Under China's AD rules, taxpayers may choose one method from shortened asset life, DDB, and SYD. We discuss the 40% reduction in asset life as the main tax benefit, although the SYD method may yield faster depreciation for long-lived assets.

[7] SMPEs are firms with (1) total assets under 30 million or 10 million CNY depending on industry, (2) total employees under 100 or 80 depending on industry, and (3) taxable income of less than 300,000 CNY.

[8] In 2019, the Chinese government extended the preferential treatment given to the 2014 and 2015 industries to all manufacturing industries, also on a permanent basis.

[9] Table 1 of Gravelle [1982] shows that the simple average (across asset classes) of the extent by which ACRS shortened asset lives was 43.67%, very close to the 40% reduction under China's AD policy.

[10] However, (i) China does not have a half-year rule and depreciation begins in the month when asset is placed in service; (ii) MACRS allows switch-over from DDB to straight-line depreciation when that is faster, but China does not.

$$Z_k = Z_{1,k} + \sum_{j=2}^{L_k} \frac{Z_{t,k}}{(1+r)^j} \tag{2.1}$$

where r is the risk-adjusted discount rate. We use a 7% rate which is used by Zwick and Mahon [2017] and Maffini et al. [2019] and likely a lower bound for Chinese firms. Table 2.2's middle three columns show that for an asset with regular asset life of 5 years ($L_k = 5$), the difference in PV between the regular and accelerated regimes is \$5.9 on a \$100 investment, which generates \$1.46 in tax savings at the standard 25% tax rate.

The second-to-last column of Table 2.2 (Panel A) shows the PV of depreciation under the DDB method. For assets of 5 years or longer, the PV of deductions is greater under shortened useful life than under DDB. This allows the calculation in the last column of an implied bonus depreciation factor relative to DDB depreciation.[11] The most favorable Chinese AD rules are thus equivalent to allowing first-year bonus depreciation at 21% or 22% (for 5- and 10-year assets), smaller than the 30% bonus factor in U.S. legislation in 2002.

To quantify AD-induced tax savings for our firm sample, we assume that each firm allocates new investment dollars in proportion to its current asset holdings. Denoting $V_{i,k}$ as firm i's holding of type k assets, the average tax value of depreciation deductions is:

$$\tau Z = \frac{1}{N} \sum_i \tau_i \sum_k \frac{V_{i,k}}{\sum_k V_{i,k}} Z_k \tag{2.2}$$

where τ_i is firm i's tax rate. While the standard tax rate in China is 25%, SMPEs faced 20% and 10% rates during this period, and High and New Technology Enterprises (HNTEs) faced a 15% rate. Using each firm's observed tax rate on their 2013 tax returns, Panel B of Table 2.2 reports that AD increased Z by \$9.5 on a \$100 investment, which is greater than the effect of bonus depreciation studied in Zwick and Mahon [2017] and that of the U.K. first-year capital allowances studied in Maffini et al. [2019]. However, tax savings (τZ) are attenuated by China's lower statutory rates: on average \$1.7 on a \$100 investment. The user cost of capital (UCC), $(1 - \tau Z)/(1 - \tau)$, declined by .022, or 2.1 percent following AD, which is on the lower bound of the benefits of bonus depreciation but higher than the U.K. first-year capital allowances. These figures quantify the effect of the preferential AD benefits that were only available to firms in the targeted industries.

Two major tax policy changes during the period we study may also have affected firms' investment decisions. The first is the lowering of the effective corporate tax rate for certain SMPEs. However, in our analysis sample, the prevalence of SMPEs is the same in the treatment and control groups, and therefore would not confound the effect of AD. The second is the expansion of the value added tax (VAT) to the service sector, which may increase the investment incentives of firms in

[11] U.S. bonus depreciation allows firms to deduct a percentage of the asset value immediately and the remaining portion according to MACRS (i.e. DDB depreciation).

service industries. In our research design, firms in both the treated and control groups are from sectors already subject to the VAT. They were thus not directly affected by the VAT expansion, and any indirect effect of VAT reform may reasonably be assumed to be common across treated and control groups.

2.2 Data and Sample Descriptions

Our analyses use a novel administrative data set from a large and prosperous province. The data is extracted from the comprehensive database used by the provincial tax agency for all of its activities, including taxpayer risk assessment and inspections. The data covers the period 2010-2016 and includes de-identified information for firms of all sizes and sectors. It contains a large number of variables from the annual corporate income tax return, income statements and balance sheets, as well as a taxpayer registry. The data is relied on by tax administrators and backed by genuine legal obligations borne by taxpayers.

Specifically, our data set includes entries on Schedule A105080 of the corporate income tax return where taxpayers report asset-specific AD. For each of five different asset classes, there are four fields that report, respectively, the sum and the individual values of three forms of AD: (1) immediate expensing; (2) AD introduced in 2014/5; and (3) the minor forms of AD in place prior to 2014/5. These fields were not available on tax returns before 2014. Schedule A105080 also reports a firm's fixed asset stock by type, which allows us to calculate asset compositions. Moreover, information from the main Schedule A100000 provides observations of firms' current tax loss positions, whether they have loss carry forwards, and their statutory tax rates. The data also includes financial statement variables, including the stock of fixed assets net of accounting depreciation.

Another novel feature of our data is that it provides a 9-digit geographic code (the neighborhood level) for each taxpayer, and identifies the tax bureau directly in charge of each firm.[12] We manually collect the physical address of each tax bureau. Using the 9-digit area code to proxy for each firm's location and combining it with the location of the tax bureau, we calculate the geographic distance between each firm and its tax bureau. We also manually search the websites of each tax bureau to obtain information on staff size.[13] Pooling all this information together, we can analyze how features of tax administration influence the effectiveness of AD.

We obtain from the tax returns 4,547 firms in the 2014 targeted industries, 17,721 firms in the 2015 targeted industries, and 8,419 firms in non-targeted manufacturing industries, for which we observe non-missing necessary financial information.

Table 2.3 provides summary statistics of key variables in our analyses for each group as of 2013. Firms in the 2015 targeted industries are similar to those in the non-targeted industries in most

[12] During the period we study, the general configuration of tax bureaus remained relatively stable.

[13] The websites do not disclose historical information on staff size by year. But assuming staff size to be highly persistent over time, the 2018 information will accurately proxy bureau resources in 2014-2016.

dimensions. Firms in the 2014 targeted industries appear more different: as they are more "high tech" than traditional manufacturing industries (Table 1), they are younger, smaller, faster growing, more likely to be an HNTE, hold more cash and are less likely to borrow[14]. For all three groups, a large proportion of firms are loss-making and carry a substantial amount of loss carry-forward.

2.3 Did AD Stimulate Investment?

2.3.1 Empirical Strategy

We start by examining whether AD's introduction stimulated investment. Since the AD provisions were more generous for the targeted than for the non-targeted industries, policy variation arises as long as investment is not mainly driven by small purchases or purchases of equipment used exclusively for R&D.[15] Denote $y_{i,t}$ as a measure of firm i's investment in year t, D_i as an indicator for being in a targeted industry, and $Post_t$ as an indicator for years after the policy implementation. Firms in 2014 targeted industries are not in the control group for the 2015 treatment, nor vice versa.[16] The baseline DiD specification is:

$$y_{i,t} = \alpha_t + \alpha_i + \beta \times Post_t \times D_i + \epsilon_{i,t,g} \tag{2.3}$$

The coefficient of interest, β, captures the difference in $y_{i,t}$ between targeted and non-targeted firms under the AD regime, relative to the difference before AD's implementation. We control for firm and year fixed effects (α_i, α_t).

Our outcome $y_{i,t}$ is based on the stock of fixed assets net of accounting depreciation. To relate changes in asset stock to investment expenditure, we assume that assets accumulate according to the following model:

$$K_t = I_t + (1 - \gamma)(K_{t-1} - S_t) \tag{2.4}$$

K_t denotes fixed assets net of accounting depreciation at the end of year t, I_t denotes new asset purchases made in t, γ is the depreciation rate on existing assets, and S_t denotes asset dispositions in t. Our first outcome variable is $Ln(K_t) - Ln(K_{t-1}) \approx \frac{K_t - K_{t-1}}{K_{t-1}} = \frac{I_t}{K_{t-1}} - \frac{(1-\gamma)S_t}{K_{t-1}} - \gamma$, which differs from I_t/K_{t-1} in two ways. First, the change in asset stock incorporates accounting depreciation γ. However, firm fixed effects will absorb γ if it is constant over time for each firm.[17] Second, our measure incorporates S_t (which we do not observe). If older assets already subject to substantial depreciation are more likely to be disposed of, S_t should be small. Under these assumptions, the

[14] As proxied by whether they claim deductions for interest payments.

[15] Few firms claimed R&D super deductions in the tax returns, which indicates infrequent R&D investment.

[16] For the 2014 targeted industries, the post period is 2014 to 2016. For the 2015 targeted industries, the post period is 2015 to 2016.

[17] Tax depreciation is distinct from accounting depreciation, so the AD policy will not directly affect γ.

estimate of β, using $Ln(K_t) - Ln(K_{t-1})$ as the outcome variable, approximates the effect on I_t/K_{t-1}. For robustness, we present results using $Ln(K_t)$ as the outcome, which measures asset accumulation rather than asset growth. This also gives us one more year before treatment that helps with testing for parallel pre-treatment trends, especially for the 2014 reform.

Table 2.3 reveals differences in observed characteristics between targeted and non-targeted firms, particularly the 2014 group.[18] We therefore construct a control group of firms more comparable with targeted firms using a two-step matching procedure. First, we restrict the control group to non-targeted manufacturing firms. Second, using Coarsened Exact Matching (CEM) [Iacus et al., 2011], we match targeted and non-targeted firms on their i) age, ii) profit margin ($\frac{\text{Total Profit}}{\text{Sales}}$), iii) total assets, and iv) revenue growth, all as of 2013.[19] By matching on pre-AD characteristics, we lessen the likelihood that treatment and control firms experience different shocks during the policy. Table A.1 in the Online Appendix reports summary statistics for the matched sets of firms both before and after matching. Before matching, the targeted and non-targeted groups are statistically different in all the matching variables in 2013. After matching, firms become more similar on both matched and unmatched characteristics.

2.3.2 Baseline Results

Figure 2.1 reports the evolution of $Ln(K_t) - Ln(K_{t-1})$ and $Ln(K_t)$ for the matched treated and control groups. We estimate a dynamic version of equation (5.2) as $y_{i,t} = \alpha_t + \alpha_i + \sum_{s \neq 2013} \beta_s \times \mathbb{1}\{t = s\} \times D_i + \epsilon_{i,t,g}$. We then plot α_t for the control group and $\alpha_t + \beta_t$ for the treatment group and the associated 95% confidence intervals.[20] For both treatment cohorts, asset growth declined during 2013-2016 consistent with China's declining GDP growth during this period.[21] Pre-treatment trends are also parallel, as best illustrated by Panels C and D.

Table 2.4 presents estimates of equation (5.2), with all coefficients scaled by 100. All regressions employ DFL re-weighting [DiNardo et al., 1996] based on total sales, a common approach for controlling for changes in the composition of firms over time [Yagan, 2015; Zwick and Mahon, 2017].[22] Standard errors are clustered at the three-digit industry level to account for within-industry correlations and serial correlation over time within a firm. Columns (1) and (2) show that AD did not lead to higher asset growth for the treated group: the point estimates in both are negative and insignificant. In columns (3) and (4), point estimates for the effect of AD on $Ln(K_t)$ are positive but statistically insignificant.

[18] Firm fixed effects α_i will account for level shifts in $y_{i,t}$ caused by these differences. but not account for differences in how firms respond to AD policy. The ideal experiment assigns different AD generosity to firms with the same investment responsiveness.

[19] Matching on age selects control firms at similar points in their life-cycle; on profit margin, firms of similar productivity; total asset stock, firms of similar size; and revenue growth, firms similar in growth trajectories.

[20] The coefficient β_t represents the difference between treated and control in year t relative to the baseline difference in 2013. Adding α_t allows us to illustrates level trends as opposed to just relative changes.

[21] China's GDP growth declined from 7.86% in 2012 to 6.85% in 2016.

[22] Online Appendix A details the construction of the weights. The results are highly similar without re-weighting.

The AD provisions available only to the targeted industries reduced the UCC by 2.1 percent. We derive an upper bound on the elasticity of the investment rate (I_t/K_{t-1}) as $\eta = \frac{\frac{\hat{\beta}_u}{I/K_{Pre}}}{.021}$, where $\hat{\beta}_u$ is the upper bound on the 90% confidence interval of β and $\frac{I}{K}_{Pre}$ is the average investment rate before the policy changes in the targeted industries. In section 2.3.1, we showed that $\frac{I_t}{K_{t-1}} = \frac{K_t - K_{t-1}}{K_{t-1}} + \frac{(1-\gamma)S_t}{K_{t-1}} + \gamma$. We observe $\frac{K_t - K_{t-1}}{K_{t-1}}$ in our data: .069 and .049 for the 2014 and 2015 groups, respectively, in the pre-AD period (Table 2.4). We do not observe $\frac{(1-\gamma)S_t}{K_{t-1}} + \gamma$, and so rely on an estimate from Qiu and Wan [2019] of .095 for the same years.[23] This allows us to estimate $\frac{I}{K}_{Pre}$: .164 and .144 for the 2014 and 2015 cohorts, respectively. The resulting 90% upper bounds on η are .1 and 6.25 for the 2014 and 2015 policies, respectively. These are below the elasticity estimates from Maffini et al. [2019] (8.3-9.9) and Ohrn [2018] (6.5).[24] Alternatively, Online Appendix A uses a two-stage least squares approach to estimate the elasticities, yielding very similar results.

We conduct a series of robustness checks in the Online Appendix A. The first four columns in Table A.3 report results using alternative outcome variables: columns (1) and (2) use the change in the capital stock, $K_t - K_{t-1}$, normalized by sales in the base period, while columns (3) and (4) use $Ln(K_t) - Ln(K_{t-1})$ with K measured at original costs from the tax return rather than net-of-depreciation from the balance sheet. Columns (5) and (6) control for linear time trends at the three digit-industry level in our baseline model. We exclude firms that claimed R&D deductions in columns (7) and (8), and remove observations where the firm was eligible for SMPE status in columns (9) and (10). In Figure A.2, we show dynamic DiD estimates from alternative specification and sample choices, including: (1) removing DFL re-weighting, (2) removing both matching and DFL re-weighting, and (3) estimating based on a balanced sample. Finally, Online Appendix A shows dynamic DiD estimates when the 2014 and 2015 treated industries are combined into a single treatment group. In all these additional checks, we continue to find little impact of AD on firm asset growth.

2.3.3 Heterogeneity Across Firms and Asset Types

To explore firm heterogeneity in responses, we first execute a series of split sample regressions. The sample splits are based on firm characteristics measured as of 2013. We then estimate equation (5.2) for each sub-sample separately, using $Ln(K_t) - Ln(K_{t-1})$ as the outcome.[25] We do this for eight firm characteristics, for both the 2014 and 2015 targeted industries, resulting in 32 estimates of β. Panel A of Figure 2.2 plots each estimate, the associated 95% confidence intervals, and the

[23] Qiu and Wan [2019] use aggregate data from the National Bureau of Statistics (NBS) to calculate depreciation rates. We average their annual rates for the period 2010 to 2013. The 9.5% reported by Qiu and Wan [2019] is similar to the 9% assumed by Liu et al. [2019].

[24] We can also compute the elasticity of capital stock with respect to the UCC changes. Based on the point estimates in columns 3-4, this elasticity is 0.57 for the 2014 reform, and 0.32 for the 2015 reform—considerably lower than the theoretical elasticity of 1 [Hall and Jorgenson, 1967], and also lower than what recent literature finds [Bond and Xing, 2015].

[25] Figure A.4 in the Online Appendix reports results using $Ln(K_t)$ as the outcome variable—the results are similar.

p-values from the test of the treatment effects being the same across the sub-samples.

The first four heterogeneity cuts are based on whether (i) the firm is in tax losses, (ii) the average life of the firm's asset portfolio is above or below the sample median, (iii) the firm's cash-to-revenue ratio is above or below the sample median, and (iv) the firm claimed interest deductions on their tax return (the last two variables proxy for cash and financing constraints). Among the 2014 treatment group, the only statistically relevant finding is that firms that claimed interest expenses responded more than those did not. Among the 2015 group, responsiveness is not different across sub-samples.

Since AD is more beneficial for long-lived assets, it should stimulate investment in long-lived assets more. The null result in Panel A of Figure 2.2 regarding asset life is thus surprising. To further explore heterogeneity by asset life, we construct $Ln(K_{i,k,t}) - Ln(K_{i,k,t-1})$ using fixed assets measured at historical cost for each of the five asset classes k and estimate equation 5.2 separately for each k.[26] Panel B of Figure 2.2 plots the estimated βs and confidence intervals. We do not detect significant heterogeneity across asset types.

A second set of heterogeneity cuts in Panel A of Figure 2.2 examines proxies for firm tax sophistication (firm size and HNTE status) and access to tax administrators. We discuss the interpretation of these characteristics further in Section 2.5. There is little consistent heterogeneity based on these sample cuts, with the exception of firm size: for both treatment groups, the estimated treatment effect appears to be bigger for larger firms.

To further explore size heterogeneity, we use pre-treatment total assets to split firms into quartiles, and estimate the treatment effect for each quartile. Figure 2.3 reports the results. Estimated treatment effects only weakly increase with firm size.[27] However, when we narrow the sample further to the largest 5% firms, we obtain a strongly positive treatment effect for the 2015 treated group and a positive but imprecise estimate for the 2014 group (less than 130 firms belong to the top 5% sample for the 2014 group). Appendix A discusses these results in more detail, including cautions that need to be exercised in interpreting them as causal evidence of investment response. We note that in both Zwick and Mahon [2017] and Maffini et al. [2019], smaller firms show greater responsiveness to AD.

2.3.4 External Validity

To ensure that the province we study is not an outlier, we present trends using a nationally representative sample of firms from the Orbis database. Orbis collects balance sheet information from Chinese firms, including the value of fixed assets net of accounting depreciation. Panels A and B of Figure A.8 plot the time trends of $Ln(K_t) - Ln(K_{t-1})$ for the targeted industries and non-targeted manufacturing firms using Orbis data. First, the nationwide data show a downward trend in $Ln(K_t) - Ln(K_{t-1})$ leading up to the treatment, mimicking the provincial trends in Figure

[26] We do not observe the net-of-depreciation value at the asset class level.

[27] Figure A.5 shows very similar results when splitting by revenue rather than total assets.

2.1 observed in our data. Second, neither figure exhibits a detectable increase in investment among firms in the targeted industries.

In concurrent work, Fan and Liu [2020] find modest treatment effects for the 2014 AD policy. Appendix A discusses in detail how their analysis differs from ours. There are four potentially significant sources of difference. First, they use a national survey of firms which comprises mostly of large and medium-size firms: the average revenue of their sample is approximately the average revenue of the top quartile of our sample. Even within their sample of already-large firms, they find that larger firms responded more. Second, their data ends in 2015, leaving only one post-treatment year. Figure A.9 shows that, in our data, treatment effects are larger if we consider only 2015, rather than 2015-2016. Third, their survey data directly reports capital expenditure. In Appendix A, we develop an approximate correspondence between the treatment effects on their outcome, $Ln(I_t)$, and ours using $Ln(K_t)$. In that framework, their estimates are within our confidence intervals. Fourth, there are differences in empirical specifications. Most importantly, Fan and Liu [2020] include service industries in the control group (we include only manufacturing firms), which produces slightly larger treatment effects in some specifications in our data.

2.4 Take-up of Accelerated Depreciation

Results from the previous section suggest that AD did not significantly stimulate investment among targeted firms. Using tax returns, we extend the investigation to the take-up of AD. We start by documenting trends in claims of AD. Denote $AD_{i,k,t}$ as the amount of AD deduction claimed by firm i for asset class k in year t. Panel A of Figure 2.4 plots the fraction of firms with positive AD amounts ($\sum_k AD_{i,k,t} > 0$). At the peak, fewer than 20% of firms reported positive AD amounts. Claims spiked in 2015, consistent with the policy announcement occurring late in 2014. Figure A.10 in the Online Appendix shows that over 80% of firms with positive AD amounts in 2015 were first-time claimers. Targeted firms have higher claim rates than control firms in all years, consistent with the broader scope of eligible assets. Table A.4 further shows claim rates in each targeted industry. The claim rate was highest in manufacturers of i) instruments, (ii) computer, communications and other electronic equipment, and (iii) special equipment–all belonging to the 2014 targeted group.

Panel B of Figure 2.4 shows the 1st to 3rd quartile values of AD deductions. The main tax advantage offered to non-targeted firms was immediate expensing on purchases with unit value of 5,000 CNY or less. Consequently, the median amount claimed by these firms is below 10,000 CNY in all years. The values of AD claimed among the 2014 and 2015 targeted firms were generally higher, especially in 2016.

Panels C and D of Figure 2.4 consider the *take-up* of AD, defined as the likelihood of claiming AD conditional on making eligible purchases. We do this at the asset class level. We define *claiming* more narrowly here as a firm reporting a positive year-over-year increase in the AD amount for a given asset class k: $C_{i,k,t} = 1$ if $AD_{i,k,t} > AD_{i,k,t-1}$.[28] We also define *investing* narrowly as a year-over-year increase in the stock of asset type k measured at original cost: $I_{i,k,t} = 1$ if $K_{i,k,t} > K_{i,k,t-1}$.[29] Take-up is claiming conditional on investing: $C_{i,k,t} = 1 \mid I_{i,k,t} = 1$. Panel C plots the average take-up rate in each year averaged over the five asset classes. Firms in the targeted industries could, in theory, have 100% take-up. However, the take-up rate ranges from 2.5% to 17.5%. Panel D shows that the low take-up rate is observed for all asset classes. Buildings and structures have the lowest take-up rates, despite being the longest-lived assets.

Imperfect take-up is present for both large-scale and small-scale investment. Figure A.11 in the Online Appendix plots the distribution of $K_{i,k,t} - K_{i,k,t-1}$ separately for $C_{i,k,t} = 1$ and $C_{i,k,t} = 0$. The distributions are similar but with a modest rightward shift for the $C_{i,k,t} = 1$ distribution. In Table A.5, we calculate the tax savings foregone on unclaimed investment. Total tax savings foregone by the 2014 and 2015 treatment groups, respectively, is 176 million CNY (30 million USD) and 543 million CNY (90 million USD). The average forgone savings per firm, for the 2014 and 2015 groups respectively, is 75,000 CNY and 57,000 CNY (12,000 and 9,120 USD). Table A.5 also indicates that the total tax revenue cost to the government due to actual AD claims is 26 million and 48 million CNY respectively.

Imperfect take-up of AD is well-documented in developed countries, though explanations for it are offered only in passing.[30] It is especially worth noting that China's AD rules are simple by comparison to advanced economies. Chinese tax law still contains neither rules for recapture of excessive deductions nor "anti-churning" rules–all rules that the U.S. had put in place by the time ACRS was adopted. Nor is there any book-tax conformity requirement that would hinder adopting tax AD. It is thus unlikely that unique aspects of Chinese law explain low AD take-up. Studies of imperfect take-up that examine compliance costs and information transmission are more likely to be germane to understanding Chinese firms' response. Kitchen and Knittel [2016] show that firms in U.S. states where tax returns are less harmonized with the Internal Revenue Code display lower take-up of bonus depreciation, suggesting that compliance costs hinder take-up. Zwick [2021], examining

[28] We choose this approach, rather than $AD_{i,k,t} > 0$, because AD reported in year t may be attributable to asset purchases from previous periods. Both methods are imperfect. In practice, all AD claims in 2014 and the majority in 2015 are first-time claims, therefore the definitions are equivalent in those years. Even in 2016, around 50% of AD claimers did not have positive AD deductions in the previous year. In line with this, we obtain similar results when claiming is defined based on $AD_{i,k,t} > 0$.

[29] Assets at the type k level are only observed at historical cost in our data. The resulting measure of investment is a conservative indicator for new purchases since a firm that simultaneously purchases a new asset and disposes of an old one may report a year-over-year decrease in the asset stock. Our benchmark estimations in the following section exclude firms that had negative "investment" but claimed AD.

[30] Wales [1966] suggests that taxpayer learning, the presence of losses or insufficient net income may all explain observed imperfect utilization of AD benefits in the US in 1950s. Many small businesses also failed to choose AD under the 1971 US Asset Depreciation Range system: accounting complexity and prior taxpayer non-compliance were suggested as possible causes [Auerbach, 1982]. Subsequent U.S. literature tended to emphasize incentives, rather than knowledge, as constraints on AD's effectiveness. For example, Gordon et al. [1987] document that U.S. individual investors adopt straight-line depreciation for 60% of their investments in structures and forgo AD benefits. They suggest that incentives for churning real property may explain the under-utilization of AD.

a different tax benefit (loss carryback), shows that take-up is affected by the professional advice firms receive. We will examine in the next section an important but often-neglected mechanism of information transmission–tax administrators–as a potential determinant of take-up.

2.5 What Affects Take-up?

We examine two complementary explanations of low take-up. One is that widespread losses, and the tax law's treatment of losses, render the benefit of AD small or even negative relative to regular depreciation. The other is that, due to poor policy publicity and a lack of prior exposure, firms were unaware or did not understand AD's benefits. We disentangle these narratives by examining how loss positions, firm tax sophistication, and tax administration influence take-up. We focus on targeted industries only. Control industries could only claim AD for a subset of investments, so their limited take-up is less informative.

2.5.1 Firm-Level Characteristics

We first examine how take-up correlates with firms' taxable income before any AD deduction is applied. Panel A of Figure 2.5 plots the take-up rate of AD against uncensored taxable income normalized by total assets.[31] We normalize taxable income by total asset stock to control for the effect of firm size on take-up. Take-up rates are less than 5% for firms in taxable loss, then begin to rise steeply with income after the zero-income benchmark. This suggests a strong negative effect of tax losses on take-up. The upward slope when taxable income is positive can be explained if normalizing by total assets is insufficient to reduce the size effect. A firm with more taxable income is also more likely to claim AD because it is less likely to have taxable losses in the future.

The present value of AD is likely to be smaller for firms with larger stock of unclaimed tax losses as they may take a longer time to become profitable. We construct the stock of unused tax losses for each firm by beginning with observed tax losses in 2010, the first period of our data, and summing the accumulation of losses thereafter. Panel B of Figure 2.5 plots the lagged stock of taxable losses against the take-up rate of AD, and shows a negative correlation between the stock of unused taxable losses and take-up.[32]

Low take-up may also reflect non-trivial compliance costs of claiming. Such costs can arise when firms must learn about new tax incentives, and when general guidance from tax authorities is limited. Firms with greater tax sophistication may be advantaged in coping with this cost. One crude measure of tax sophistication is the size of a firm–larger firms are more likely to employ dedicated accountants and tax experts. Panel C of Figure 2.5 shows a strong positive correlation

[31] We define uncensored taxable income as total book profit reported on the tax return plus the net value of book-tax adjustments (excluding AD adjustments) minus exempt income and claimed loss carry-forwards.

[32] In China, tax losses generally can be carried forward for only five years and not back, a much less generous treatment than in other countries. This suppresses the incentives of firms with large unused tax losses to claim AD.

between the firm's total assets and take-up. Alternative measures of firm size such as business revenue yield similar results.[33]

Prior experience with complex tax incentives may also enhance firms' tax sophistication. In China, various tax incentives given to firms with HNTE status pre-date AD policy [Chen et al., 2020c]. To obtain HNTE status, firms need not only to satisfy requirements based on R&D intensity, but also to comply with extensive procedures for claiming tax benefits. Such firms are likely to have invested in the capacity to claim tax preferences and thereby better-positioned to take advantage of new incentives. Consistent with this conjecture, Figure 2.5 Panel D shows that HNTEs are twice as likely to claim AD than non-HNTE firms.[34]

Finally, the absolute value of claiming AD grows with the size of investment. In the presence of fixed costs of claiming AD, the probability of claiming should rise with investment size. Consistent with this hypothesis, as shown previously, Figure A.11 in the Online Appendix shows a modest positive relationship between investment size and take-up.

We jointly estimate how these covariates $X_{i,t}$ predict take-up. We restrict to firms with $I_{i,k,t} = 1$, estimate a probit model of $C_{i,k,t}$, and present estimates of the average marginal effects: $\frac{\partial P(C_{i,k,t}=1|I_{i,k,t}=1)}{\partial X_{i,t}}$. The goal is to examine the predictors of take-up in a reduced-form manner without fully-specifying the dynamic nature of investment and claiming decisions. As an extension, we estimate a selection model that accounts for some forms of selection bias that could arise due to correlated propensities to both invest and claim AD.

Table 2.5 presents the results. All columns report average marginal effects scaled by 100.[35] Columns (1) and (2) report the estimated effects of each firm characteristic on the conditional probability of claiming. Column (1) includes two-digit industry, year, and asset class fixed effects. Column (2) adds prefecture fixed effects to control for geographic variation. Confirming the graphical evidence, losses negatively predict take-up. Based on column (2), firms in current year loss positions (before AD deductions) are 2.85 percentage points (p.p), or 45 percent (2.85/6.36), less likely to claim AD on eligible investments. The stock of unused tax losses at the end of the previous year also negatively correlates with take-up probability.

Results regarding proxies for tax sophistication also confirm the graphical evidence. Column (2) indicate that a 100% increase total asset stock is associated with a 0.63 p.p. increase in the probability of claiming on a base claiming rate of 6.36%. HNTE firms are 1.8 p.p (28%) more likely to claim AD relative to non-HNTE firms. A doubling of the size of eligible investment $(K_{i,k,t} - K_{i,k,t-1})$

[33] As a by-product of large firms better availing themselves of AD's tax savings than small firms, the policy creates a size-based benefit. Figure A.12 in the Online Appendix plots the average ratio of tax savings from AD over firm revenue, across the firm size distribution. Tax savings among the largest firms is almost double that of the smallest firms.

[34] While HNTE firms face a lower statutory rate, they are also frequent users of a 50% super-deduction for R&D related expenses. Such super-deduction would raise the value of one additional dollar of AD to a level similar to other taxpayers.

[35] Standard errors are computed using the delta-method and clustered at the two-digit industry level.

increases the take-up probability by .09 p.p.[36]

By restricting to firms with $I_{i,k,t} = 1$, selection bias could arise if the idiosyncratic propensity to invest is correlated with the propensity to claim AD. In column (3), we examine whether accounting for such selection matters by implementing the standard two-stage choice model [Heckman, 1979](discussed in Online Appendix A). If there is selection bias, the estimates presented in column (3) should differ from those in column (2). However, the point estimates are mostly unchanged.

2.5.2 The Role of Tax Administration

AD was a new policy in China and less straightforward than tax rate cuts. Consequently, the policy may have lacked salience for most firms. In this context, while firms' own tax sophistication affect the take-up of AD, tax administrators could also play a crucial role. In addition to ensuring taxpayer compliance, China's front-line tax administrators are responsible for informing taxpayers of the content of tax law [Cui, 2015]. Indeed, most taxpayers rely on officials in nearby tax offices instead of third-party professionals to learn about rules applicable to their businesses. Major tax policy changes are commonly accomplished by campaigns to spread knowledge of the changes among taxpayers. Disseminating information about policies that are politically important are often a part of civil servants' performance metrics. In contrast, general media coverage of tax policies is weak.[37] For all these reasons, tax administrators role in transmitting policy information takes on singular importance.

We consider two aspects in tax administration that potentially bear on policy information transmission: geographical distance between firms and their assigned tax bureaus, and the staffing level of each bureau. First, information transmission may be weakened if firms and tax administrators are distant from each other. Proximity to regional tax offices has been used in research in other countries as a proxy for the degree of information transmission from tax administrators to firms [McKenzie and Seynabou Sakho, 2010]. Though Chinese tax agencies began to make extensive use of social media and smart phone apps to publicize policies in recent years, such use was not yet prevalent in the years we study.[38] This leads to our first hypothesis that being located closer to the local tax bureau increases the awareness and therefore use of tax incentives. In our data, each firm is assigned to the jurisdiction of a tax bureau. Utilizing the area codes of the firm and its local tax bureau, we calculate the geographic distance for each firm-bureau pair.[39] Figure A.13 in the Online Appendix presents the histogram of measured distances in our sample, which displays rich variation across firms.

[36]Since our measure of investment based on changes in asset stock is conservative, the estimated effect of investment size on take-up is likely attenuated downwards.

[37]The adoption of tax policy in China largely bypasses legislatures and the legal system, and consequently lacks the venues of publicity and outreach that tax policies possess in democratic countries.

[38]Even today technologies often complement, instead of substitute for, in-person taxpayer services.

[39]We observe the firm's bureau assignment as of 2017. Firms generally do not change this assignment. However, if some bureaus changed location between 2014 and 2016, then the 2017 information will contain measurement error.

Second, information delivery is likely to be constrained by the resources of local tax bureaus. We obtained data on the number of staff for a subset of local tax bureaus, available from their official websites. We divide this number into the number of firms assigned to the bureau in 2013. A higher ratio of firms to bureau staff in a given jurisdiction suggests a greater workload for administrators and weaker capacity to provide guidance to firms. This, in turn, may predict lower take-up.

Panels E and F of Figure 2.5 plot the correlation between take-up and the two tax bureau characteristics, respectively. Consistent with both hypotheses, firms further away from their bureaus have lower claim rates, as do firms assigned to lower-resourced tax bureaus. Table 2.6 presents estimates of the average marginal effects of these two proxies. All columns control for the firm characteristics in Table 2.5 and two-digit industry fixed effects. We also control for prefecture fixed effects to account for unobservable geographic factors that affect take-up. Column (3), our baseline specification, shows that a 100% increase in staffing predicts a 1.89 p.p., or a 27 percent (1.89/6.85), increase in take-up. A 100% increase in distance predicts a 0.76 p.p, or 11 percent, decrease in take-up.

A firm's distance to its local tax bureau may correlate with the proximity to other important government institutions. As a placebo test, we examine whether take-up correlates with the firm's distance to the nearest district or county People's Government office (the executive branch's central office). Column (4) shows that the estimated effect of this placebo is indistinguishable from zero. This corroborates the view of local tax bureaus as the relevant source of tax-related information. Additionally, in Column (5), we include tax bureau fixed effects such that the effect of distance is identified solely on within-bureau variation. The estimated effect is largely unchanged.

One concern is that less tax-compliant firms may be less likely to respond to tax incentives [Fan and Liu, 2020] and may also locate further from tax bureaus. In column (6), we include three indicators of firms' non-compliance tendency: the gap between the firm's statutory tax rate (STR) and their measured effective tax rate (ETR), the ratio of fixed assets to total assets, and the ratio of profits to business revenue. Firms with much lower ETR than STR may be less compliant; firms with more fixed assets may be more compliant since it is easier to verify their assets [Gordon and Li, 2009]; and more profitable firms may be more compliant [Cai and Liu, 2009]. While these are only rough proxies for tax compliance, column (6) shows that none predicts take-up. Nor does including them in the regression materially change the estimated coefficients on the tax administration variables.[40]

Another possible confounding factor is that firms located in industrial parks, or in urban areas, may have more opportunities to learn about AD from other firms. Tax offices may also be set up specifically in such locations to deal with greater demand. In column (6), we include indicators for whether a firm is located in an industrial park or in an urban area. Neither are significantly associated with take-up.

Finally, firms with lower tax sophistication should benefit more from increased access to tax

[40]In Table A.6 of the Online Appendix, we do not find evidence that firms located further away from tax offices, or those facing a higher ratio of firms to tax bureau staffs, are more likely to avoid tax.

administrators, while firms with greater tax sophistication should be less affected. To test this, column (7) interacts the tax administration variables with an indicator for HNTE status. We expect HNTE firms to be less reliant upon tax administrators for understanding AD. Indeed we find the marginal effects of both bureau staff resources and firm distance to tax bureaus attenuated towards zero for HNTE firms.

2.5.3 Local Accounting Resources

External tax professionals help firms optimize tax strategies [Zwick, 2021]. We use two measures of local accounting resources to proxy firms' access to third-party tax expertise. The first is the number of accountants among the working population in each district.[41] The second is the ratio of accounting firms to the total number of firms in each district. We obtain information on accounting firms and their physical addresses from a certified online platform that provides information on companies' registration and credit record. Table A.7 shows the effects of each measure on take-up. The estimated coefficients on accountants per worker and on accounting firm density in the same area are both statistically indistinguishable from 0. Somewhat puzzling, there is a negative and significant association between take-up and the ratio of accountants per firm in our tax data. Overall, these results suggest that external accounting resources are less important in China than in the US. This further highlights the role of local tax administration in information transmission.

2.5.4 Did Knowledge Lead to Greater Investment?

Our analysis suggests that information frictions were a primary driver of low take-up. If such frictions were ameliorated, would investment responsiveness have increased? One way to address this question is to test whether traits that make firms better informed also predict greater investment responsiveness (β from equation (5.2)). Returning to Panel A of Figure 2.2, the last eight rows present split-sample estimates of β for four proxies of policy awareness: HNTE status, firm size, distance to a tax bureau, and tax bureau resource level. Neither tax administration measure predicts greater investment responsiveness, nor does HNTE status. There is, however, weak evidence that larger firms responded more positively. As reported in Section 2.3.3, only the largest 5% of firms in the targeted industries appear to have increased investment significantly, relative to comparable control firms. These firms are also more likely to claim AD (See Figure A.7 in the Online Appendix). Thus, AD appears to have been more effective for this small group of very large firms.

We can also examine whether, regardless of size, firms that claimed AD on their tax returns experienced greater asset growth relative to non-claimers. Claimers overcame information frictions at least during tax filing. But firms that invested due to non-tax reasons may also be more likely to claim AD whereas firms without investment, by definition, cannot. This creates a positive selection bias, making the comparison descriptive rather than causal. We estimate the following DiD model:

[41] We calculate these based on the 2010 Population Census conducted by the National Statistics Bureau.

$$y_{i,t} = \alpha_t + \alpha_i + \sum_{s \neq 2013} \theta_s \times \mathbb{1}\{t = s\} \times C_i + \epsilon_{i,t,g} \tag{2.5}$$

where C_i is one if the firm reported positive AD deductions any time after the treatment. Figure 2.6 plots θ_s for two samples: the full set of treated firms and the subset of treated firms with positive asset growth ($K_t > K_{t-1}$) at least once during the AD years. A positive θ_s in the post-treatment years could be driven either by selection where firms claim AD on infra-marginal investment, or by AD-induced increases in investment. Restricting to firms with $K_t > K_{t-1}$ partially controls for the selection effect. In Panels A and B where the outcome variable is $Ln(K_t) - Ln(K_{t-1})$, we observe that θ_s is indistinguishable from zero in all years. In Panels C and D where the outcome variable is $Ln(K_t)$, the comparison between claimers and non-claimers in general displays pre-treatment trends. Conditional on positive asset growth, claimers and non-claimers are not different. Thus, the average claiming firm most likely claimed AD on inframarginal investment.

Overall, our analyses indicate that knowledge of the AD incentive alone was insufficient to stimulate investment for most firms. Other factors may have rendered the policy ineffective. China's GDP growth slowed considerably during our sample period and there was high economic uncertainty [Huang and Luk, 2020], which could dampen investment incentives [Guceri and Albinowski, 2021]. Larger firms have more resources to cope with such an uncertain environment [Ghosal and Loungani, 2000], but for the vast majority of smaller firms, it could have been difficult for AD incentives to overcome such drags on investment, even if awareness increased. Nonetheless, even within the top 5% of firms with positive asset growth, the claiming rate of AD is mediocre (less than 40%), indicating substantial information friction. Hence, improving the salience of AD incentives even just among large firms may be fruitful.

2.6 Conclusions

Using confidential corporate tax returns from a large province, we document that the introduction of AD in China failed to meaningfully stimulate investment, in contrast to recent studies of similar policies in the US and UK. We further document that firms did not claim AD on over 80% of cases of eligible investments. Tax losses, tax sophistication, and access to tax administration all strongly predict firms' likelihood of taking up AD benefits.

Our findings–in terms of both the low take-up for a significant tax benefit, and the impact of tax administrator accessibility on such take-up–are likely not unique to the Chinese context. Imperfect take-up of AD been documented in other countries (see Section 2.4 above). It is also well-recognized that the accounting and legal professions play an important role in transmitting information about the content of law and policy [OECD, 2019]. The success of such professions, however, likely depends on the existence of sizeable populations of firms that are sufficiently large and profitable to outsource compliance tasks. In less developed countries, these professions tend not to flourish. This sharply reduces available channels for policy information transmission. Tax administrators may become the main “tax professionals” disseminating tax knowledge. Where professional resources are even less abundant than in China, tax administrators may play a still more crucial role in educating taxpayers.

One response to constraints on information transmission about tax policy is to make tax law less complex. But there are limits on how “simplified” tax law can become. Restricting tax policy instruments only to tax rate variations clearly has disadvantages. The Chinese AD policy and the tax return schedule on which AD benefits are claimed are already relatively simple. If taxpayers fail to apply even simple rules, it may be important to examine instead how tax law information can be more effectively transmitted. The use of newly available digital technology is certainly one direction for exploration [OECD, 2019]. Designing incentives for tax administrators so that they are adequately motivated to educate taxpayers even while trying to raise revenue is another possible direction. Both take on special significance when traditional types of tax professionals may not easily materialize.

Table 2.1: **Policy Overview**

	Unit Value < 5000	5000 < Unit Value < 1 Million	Unit Value > 1 Million
Targeted Industries	Immediate expensing for all fixed asset purchases	(1) Accelerated depreciation for all fixed asset purchases (2) Immediate expensing for equipment that is used exclusively for R&D *(3) Small Firms Only:* Immediate expensing for equipment that is shared for R&D	Accelerated depreciation for all fixed asset purchases
All Firms	Immediate expensing for all fixed asset purchases	Immediate expensing for equipment that is used exclusively for R&D	Accelerated depreciation for equipment that is used exclusively for R&D

2014 Targeted Industries
Biopharmaceutical manufacturing
Manufacturing of professional equipment
Manufacturing of railway, vessel, aerospace and other transportation equipment
Manufacturing of computer, communication, and other electronic equipment
Manufacturing of instruments and apparatus
Information transmission, software, and information technology services
2015 Targeted Industries
Light industry; Textile; Machinery; Automobile
Non-Targeted Manufacturing Industries
Wine, beverage, tea, and tobacco processing and manufacturing
Petroleum processing, coking and nuclear fuel processing
Chemical raw materials and chemical manufacturing
Rubber and plastic products industry
Non-metallic mineral products industry
Ferrous and non-ferrous metal smelting and rolling processing industry
Other Manufacturing
Waste resource comprehensive utilization industry
Metal products, machinery and equipment repair industry

Note: This table illustrates the provisions for AD and immediate expensing implemented in 2014 and 2015 and lists the set of targeted industries and non-targeted manufacturing industries. Section 2.1 describes the AD provisions for the targeted industries.

Table 2.2: **Depreciation schedules and Cost of Capital Changes**

Panel A: Regular and Accelerated Asset Depreciation Schedules

	Asset Life		PV Deductions ($r = 7\%$)				Implied BD Factor
Assets	Regular	AD	Regular	AD	Diff.	DDB	
Buildings and Structures	20	12	0.566	0.708	0.142	0.643	N.A.
Production Equipment	10	6	0.752	0.850	0.098	0.808	0.220
Furniture, Tools, Appliances	5	3	0.877	0.936	0.059	0.919	0.210
Transportation	4	3	0.906	0.936	0.030	0.945	N.A.
Electronic Equipment	3	2	0.936	0.967	0.031	0.971	N.A.

Panel B: Average Change in Cost of Capital in Tax Data Sample

	China			Recent Studies	
	Regular	AD	Change	Change in Zwick (2017)	Change in Maffini (2019)
Z	.741	.836	.095	.048 to .078	.033
τZ	.132	.150	.017	.017 to .027	.011
$\frac{1-\tau Z}{1-\tau}$	1.060	1.038	-.022	-.026 to -.042	-.016

Note: Panel A illustrates the depreciation schedules for each asset class. The first two columns show the asset lives for each asset class under the regular depreciation schedule and the AD schedule introduced in 2014 and 2015. The next three columns show the present value (PV) of deductions for a dollar of investment under the regular depreciation schedules, the AD schedule, and the difference between the two. We use a discount rate of 7%. The sixth column reports the PV of depreciation using the double declining balance (DDB) method and assuming there is no salvage value. This approximates U.S. MACRS but ignores the half-year rule and the switch to straight-line depreciation allowed under U.S. law. Lastly, we calculate the implied bonus depreciation (BD) factor obtained by equating the PV of depreciation under BD + DDB to that under AD. We only calculate this for the 5-year and 10-year assets, since U.S. BD is not available for the 20-year asset, and DDB is faster than AD for 3- and 4-year assets. Panel B quantifies the effect of the regular and AD schedules at the firm level. The first row reports the average PV of depreciation deductions (Z) with and without AD. The second row reports the PV of the tax savings due to these deductions (τZ). The third row presents estimates of the UCC under each depreciation scheme ($\frac{1-\tau Z}{1-\tau}$). We assume that each firm allocates a dollar of new investment in proportion to their pre-AD asset holdings. Denoting $V_{i,k}$ as firm i's holdings of type k assets, define $Z_i = \sum_k \frac{V_{i,k}}{\sum_k V_{i,k}} Z_k$ and $Z = \frac{1}{N}\sum_i Z_i$, where Z_k is the PV of deductions for a dollar of investment in asset class k. We define τZ as $\frac{1}{N}\sum_i \tau_i Z_i$ where τ_i is firm i's tax rate. Similarly, $\frac{1-\tau Z}{1-\tau}$ is the average across firms of $\frac{1-\tau_i Z_i}{1-\tau_i}$. Our calculations of Z under AD are based on the 40% reduction in useful life provisions for purchases greater than 5,000 CNY in the targeted industries. The calculations ignore immediate expensing on purchases of less than 5,000 CNY and the immediate expensing provisions for R&D-related purchases. The last two columns report the analogous figures for AD policies studied in Zwick and Mahon [2017] and Maffini et al. [2019].

Table 2.3: **Full Sample Descriptive Statistics 2013**

	Non-Targeted Industries		2014 Targeted Industries		2015 Targeted Industries	
	Mean	N	Mean	N	Mean	N
Total Assets	5516	8419	3649	4547	4497	17721
Fixed Assets Net of Depreciation	468	8419	298	4547	417	17721
Fixed Assets Historical Cost	1529	8419	902	4547	1350	17721
Average Useful Life	11.41	7114	8.88	3311	11.56	15620
Business Revenue	4699	8384	2188	4510	3403	17670
Revenue Growth	-.06	7940	.12	4092	-.04	16895
Taxable Income	114	8418	128	4547	80	17721
Percent In Tax Losses	.28	8419	.4	4547	.27	17721
Tax Loss Stock	227	2510	81	1867	166	5109
Cash Holdings / Total Assets	.11	8417	.26	4544	.11	17716
Claimed Interest	.29	8419	.2	4547	.33	17721
Age	15.99	8419	10.52	4547	15.76	17721
Employees	65.4	8419	50.09	4547	74.04	17721
State or Collectively Owned	.12	8419	.04	4547	.08	17721
High and New Tech Enterprise	.08	8419	.14	4547	.06	17721
Small or Micro Enterprise (SME)	.61	8419	.66	4547	.61	17721
Distance to Tax Bureau (km)	12.98	6869	9.16	3222	12.64	14437
Firms per Tax Administrator	206	6740	270	3119	250	14719

Note: This table displays means for select firm characteristics among targeted industries and manufacturing firms in non-targeted industries for the full sample of firms observed in 2013. Total Assets, Fixed Assets, Business Revenue, Taxable Income, and Tax Loss Stock are all in CNY10,000s. The mean of Tax Loss Stock is calculated conditional on having a positive amount. The average asset life duration is calculated among the subset of firms with positive reported values for at least one asset type. All continuous variables are winsorized at the 1st and 99th percentiles within each group of firms.

Table 2.4: **Did AD Stimulate Growth in Firms' Asset Stock?**

	$Ln(K_{i,t}) - Ln(K_{i,t-1})$		$Ln(K_{i,t})$	
	(1)	(2)	(3)	(4)
	2014	2015	2014	2015
Treat × Post	-3.45	-0.59	1.20	0.68
	(2.10)	(1.50)	(3.45)	(3.04)
	[-6.95,0.04]	[-3.07,1.89]	[-4.54,6.95]	[-4.35,5.71]
N	10013	34304	12890	44252
Treated Firms	1055	5868	1078	6030
Untreated Firms	1583	3208	1638	3308
Dep. Var Mean	6.90	4.85	1447.05	1454.85

Note: This table reports the estimated treatment effects based on Equation (5.2). In columns (1) and (2) the outcome variable is $Ln(K_t) - Ln(K_{t-1})$. In columns (3) and (4) the outcome is $Ln(K_t)$. Both are winsorized at the 1st and 99th percentiles within each year separately for the treated and control groups. The coefficients are scaled by 100. The 90% confidence interval is shown in square brackets. Standard errors are clustered at the three-digit industry level and shown in parenthesis. There are 44 clusters in the control groups, and 38 and 90 clusters in the 2014 and 2015 treated groups, respectively. The average of the outcome variable for the pre-treatment period (2011 to 2013) among the treated industries is shown in the "Dep. Var. Mean" row and scaled by 100. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.5: **Predictors of Claiming: Firm-Level Characteristics**

	Pr(Claim | Invest)		
	(1)	(2)	(3)
	Probit Model		Selection Model
In Tax Loss Before AD	-2.79***	-2.85***	-2.73***
	(0.45)	(0.43)	(0.43)
Ln(Tax Loss Stock $_{t-1}$)	-0.09***	-0.08**	-0.08**
	(0.03)	(0.03)	(0.03)
Ln(Total Assets $_{t-1}$)	0.56***	0.63***	0.42***
	(0.11)	(0.11)	(0.14)
High and New Technology Enterprise	2.24***	1.80***	1.83***
	(0.61)	(0.58)	(0.59)
$Ln(K_{t,k} - K_{t-1,k})$	0.12***	0.09**	0.09**
	(0.04)	(0.04)	(0.04)
Two-Digit Industry FE	Yes	Yes	Yes
Prefecture FE	No	Yes	Yes
N	48663	48663	171846
Mean of Outcome Var.	6.36	6.36	6.36

Note: This table reports the estimated average marginal effects of firm-level characteristics on the probability of claiming AD conditional on having purchased eligible investment ($P(C_{i,t,k} = 1|I_{i,t,k} = 1)$) as outlined in Section 2.5. Columns (1) and (2) present estimates from the probit model and column (3) reports estimates from the selection model, both described in Section 2.5. Coefficients are scaled by 100. All time-varying explanatory variables are measured in year $t-1$. Ln(Tax Loss Stock $_{t-1}$) is the natural logarithm of (Tax Loss Stock $_{t-1}$ +1) to account for zeros. All continuous covariates are winsorized at the 1st and 99th percentiles within each year. Standard errors are computed using the delta-method and are clustered at the three-digit industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

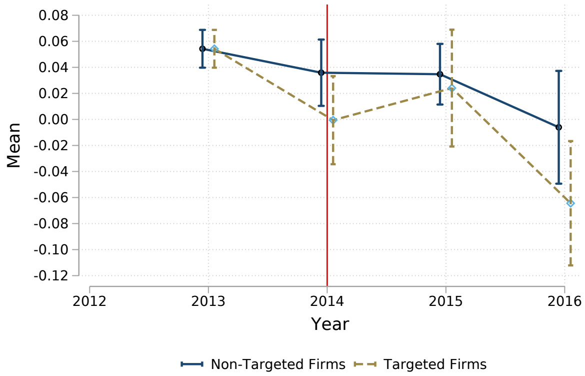
Table 2.6: **Predictors of Claiming: Tax Administration**

	Claim | Invest						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln(# Firms / # Tax Administrators)	-0.95***		-1.89***			-1.91***	-1.95***
	(0.23)		(0.35)			(0.44)	(0.36)
Log(Distance to Tax Bureau)		-0.40**	-0.76***		-0.48**	-0.73**	-0.99***
		(0.20)	(0.26)		(0.21)	(0.28)	(0.33)
Log(Distance to Government Office)				0.24			
				(0.18)			
Firm Headquarters in Industrial Park						0.43	
						(0.64)	
Urban Bureau						-0.24	
						(0.64)	
STR minus Cash ETR						-0.85	
						(0.57)	
Fixed Assets / Total Assets						0.85	
						(0.80)	
Total Profit / Business Revenue						0.57	
						(0.38)	
Ln(# Firms / # Tax Admin.) × HNTE							0.28
							(0.58)
Ln(Distance to Tax Bureau) × HNTE							0.98
							(0.69)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Two-Digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Tax Bureau FE	No	No	No	No	Yes	No	No
N	42905	40841	34374	46693	40360	32140	34374
Claim Rate	6.59	6.65	6.85	6.31	6.73	6.90	6.85

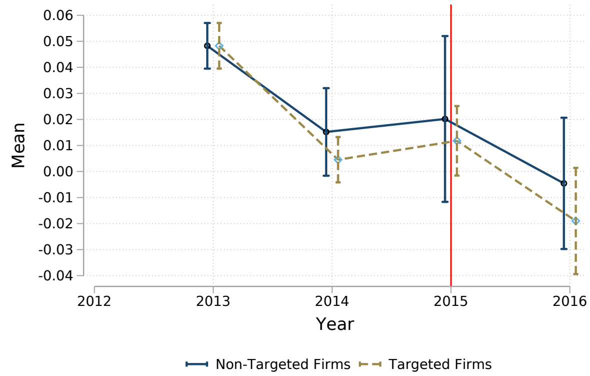
Note: This table reports the estimated average marginal effects of tax bureau characteristics on the probability of claiming AD conditional on having purchased eligible investment ($P(C_{i,t,k} = 1 | I_{i,t,k} = 1)$) using the probit model described in Section 2.5. Coefficients are scaled by 100. All continuous covariates are winsorized at the 1st and 99th percentiles within each year for each of the treatment groups. Standard errors are computed using the delta-method and are clustered at the three-digit industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 2.1: **Growth of Fixed Assets Net of Depreciation**

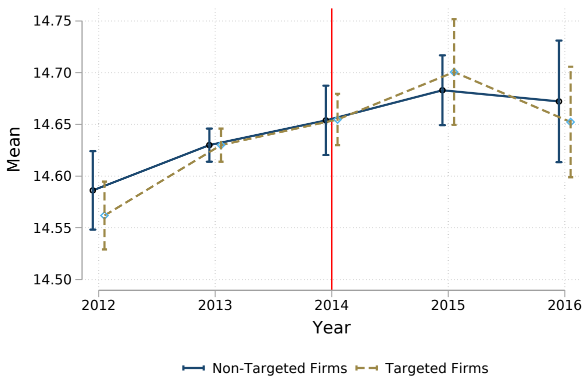
a **2014 Policy Change:** $Ln(K_t) - Ln(K_{t-1})$



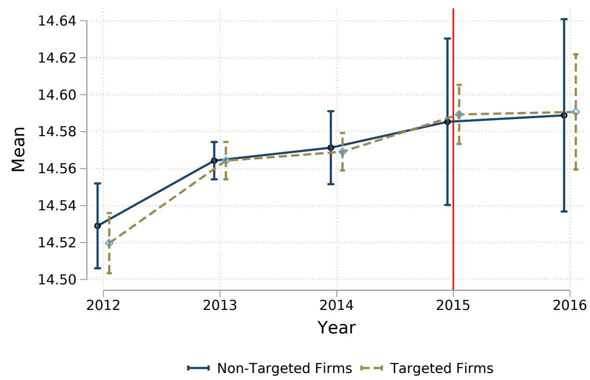
b **2015 Policy Change:** $Ln(K_t) - Ln(K_{t-1})$



c **2014 Policy Change:** $Ln(K_t)$



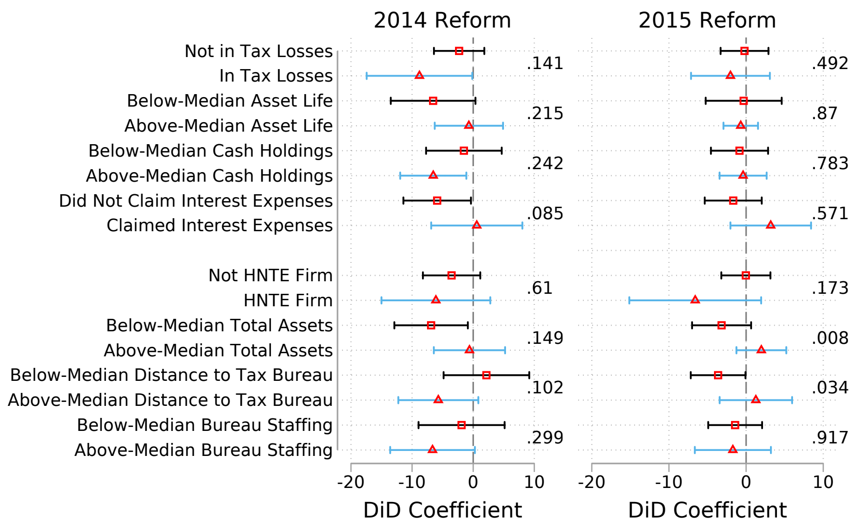
d **2015 Policy Change:** $Ln(K_t)$



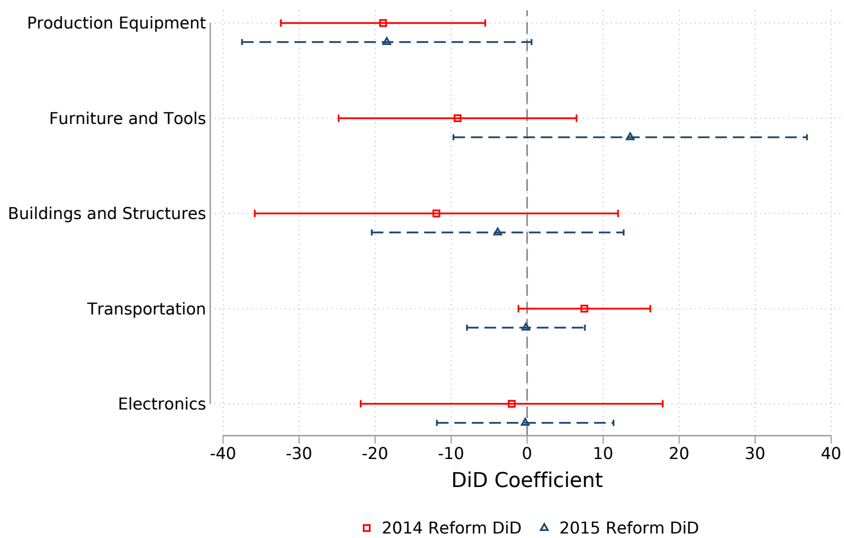
Note: Panels A and B plot trends in $Ln(K_t) - Ln(K_{t-1})$ while Panels C and D plot trends in $Ln(K_t)$. In all four, K is fixed assets net of accounting depreciation as reported on balance sheets. Trends are plotted separately for the matched treated and control firms. The control firms are those in non-targeted manufacturing industries and matched as described in Section 2.3. For each panel, we estimate a dynamic version of equation (5.2) as $y_{i,t} = \alpha_t + \alpha_i + \sum_{s \neq 2013} \beta_s \times \mathbb{1}\{t = s\} \times D_i + \epsilon_{i,t,g}$. We then plot α_t for the control group and $\alpha_t + \beta_t$ for the treatment group and the associated 95% confidence intervals. The vertical red lines indicate the timing of the AD policy announcement and implementation.

Figure 2.2: **Heterogeneous Responses to the Reform?**

a **By Firm Characteristics**



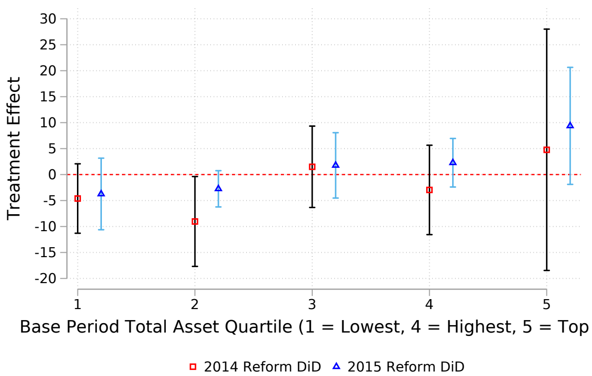
b **By Asset Type**



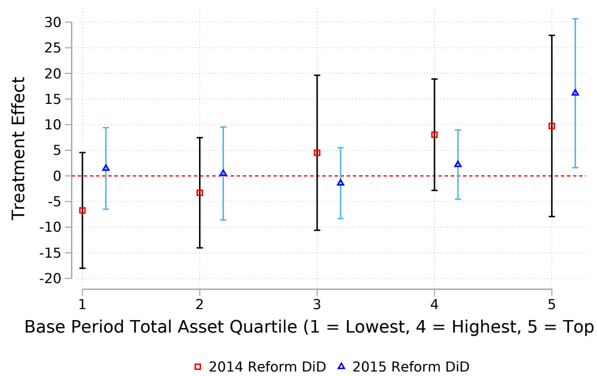
Note: Panel A plots estimates of β and 95% confidence intervals from equation (5.2) for subsets of the sample. For each of eight different firm characteristics X, we split the sample into above and below median when X is continuous, or by $X = 0$ and $X = 1$ when X is binary. The first four characteristics proxy for a firm's readiness to invest, and the how beneficial AD is for the firm. The last four characteristics proxy for a firm's informational awareness and sophistication. P-values for the test of the treatment effects being the same across sub-samples are displayed to the right of the confidence intervals. Panel B plots estimates of β for the full sample of firms but estimated separately for each asset class. In both panels, the outcome is $Ln(K_t) - Ln(K_{t-1})$. In panel A, K is fixed asset stock measured net of accounting depreciation from balance sheets. In Panel B, since net-of-depreciation measures are not observed at the asset level, K is measured at original cost from tax depreciation return, and the unit of observation is an asset type-firm-year triplet. Estimates are scaled by 100 to be consistent with the estimates reported in Table 2.4.

Figure 2.3: **Responsiveness by Pre-Reform Asset Quartiles**

a **Outcome:** $Ln(K_t) - Ln(K_{t-1})$



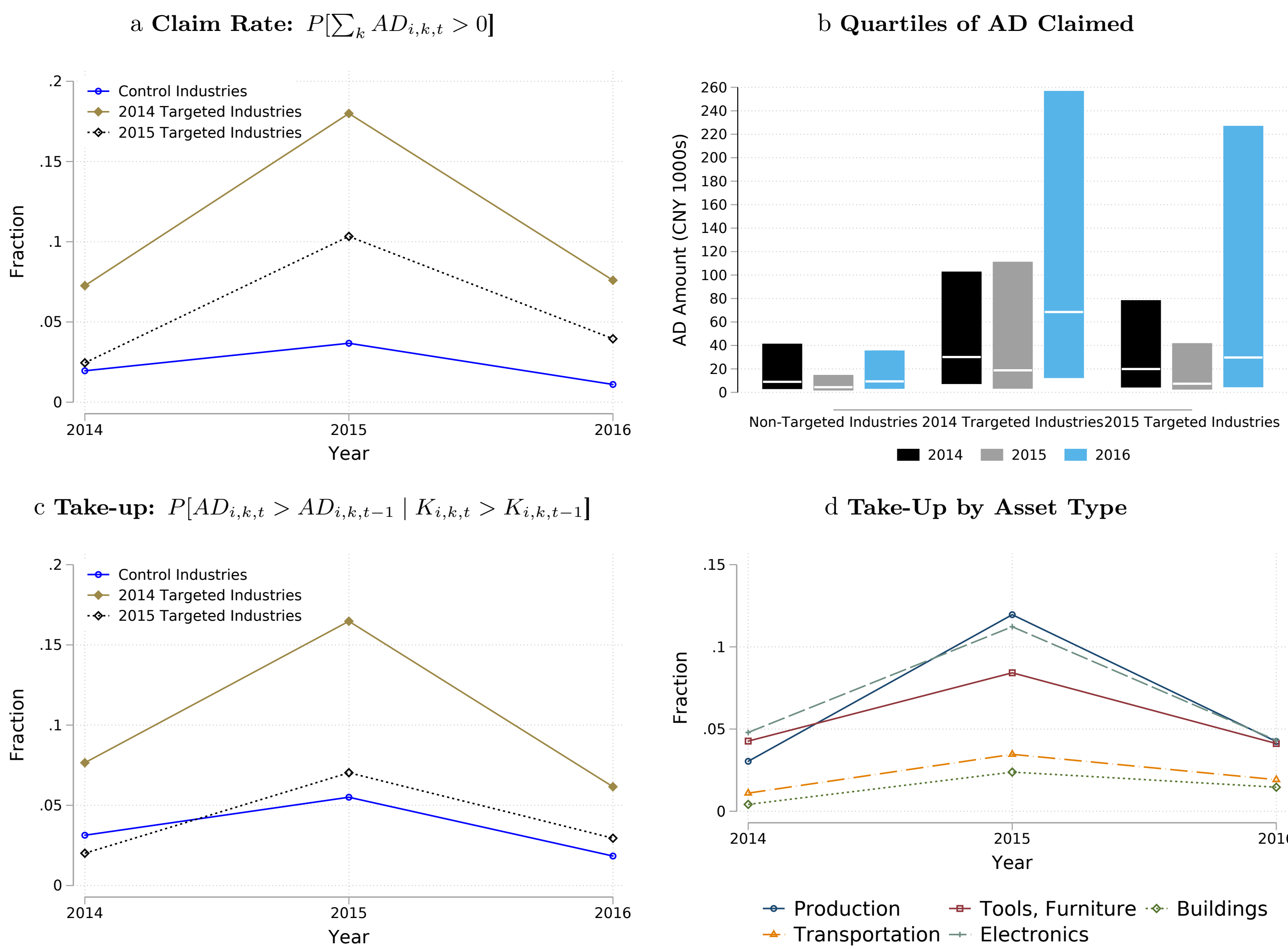
b **Outcome:** $Ln(K_t)$



Quartile	Left Endpoints		Number of Firms	
	2014	2015	2014	2015
1	0.00	0.00	666	2318
2	6.13	5.39	669	2287
3	16.18	13.25	655	2244
4	53.98	40.09	653	2227
5	381.68	295.88	128	444

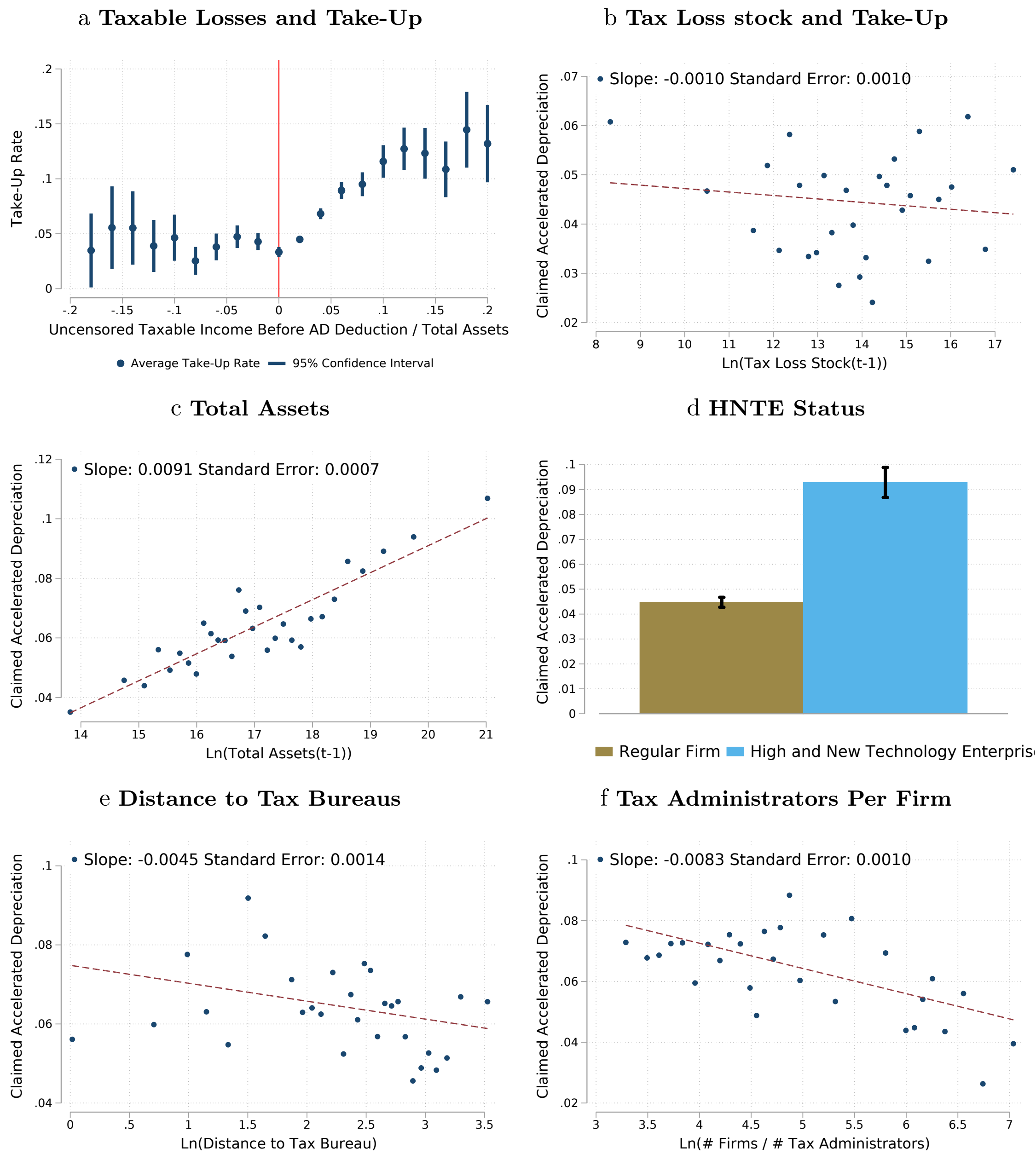
Note: Panels A and B split firms into quartiles based on pre-treatment average total assets (1 = smallest, 4 = largest). Each then plots estimates of β from equation 5.2 and 95% confidence intervals for each quartile. The fifth bin (5) plots β for the largest 5% of firms. Estimates are scaled by 100 to be consistent with the estimates reported in Table 2.4. K_t is fixed assets net of accounting depreciation. The table lists the quartile's left-endpoints, in 1,000,000CNY, and the number of firms in each.

Figure 2.4: **Take-Up of Accelerated Depreciation**



Note: This figure plots AD claiming trends during the period 2014-2016. Firms are divided into the 2014 targeted group, the 2015 targeted group, and the non-targeted group. Panel A plots the percent of firms within each group that claimed AD in at least one asset class. Panel B plots the median and interquatile range of AD amounts claimed. The top and bottom of the bars indicate the 25th and 75th percentiles, respectively, and the white divider on each bar denotes the median. Panel C calculates the take-up rate conditional on having eligible investment. For each asset class, we restrict to firms with a year-over-year increase in the asset stock (at historical cost), then calculate the percent with a year-over-year increase in AD deductions. We then average this take-up rate across the five asset classes. Panel D plots the take-up rate within each asset class.

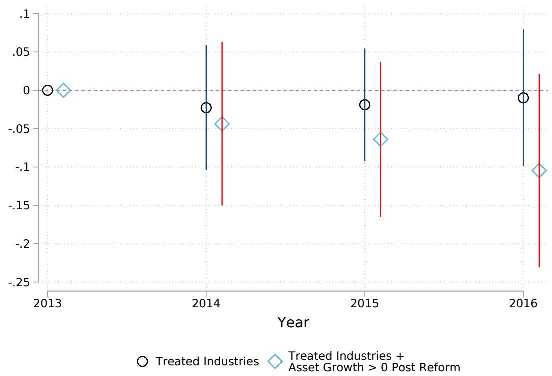
Figure 2.5: **Predictors of AD Take-Up**



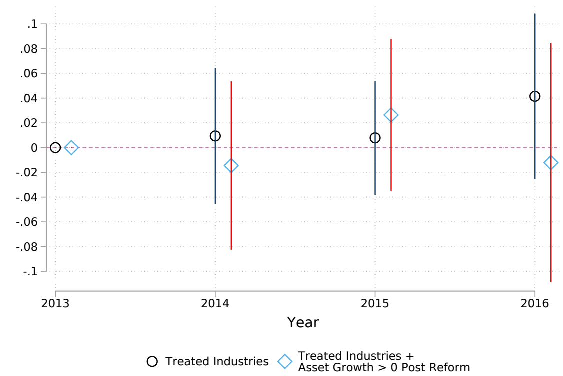
Note: This figure restricts the sample to firms that belong to the 2014 or 2015 targeted industries. Each observation is a firm-year-asset type triplet. Within each triplet, we retain firms with an increase in the asset stock relative to the previous period. Panel A plots the probability of claiming any AD against uncensored taxable income dived by total assets. Panels B through E plot the correlation between take-up of AD and a firm characteristic (both described in the main text) after controlling for two-digit industry, asset type, and year fixed effects.

Figure 2.6: **Growth of Fixed Assets by Claiming Status**

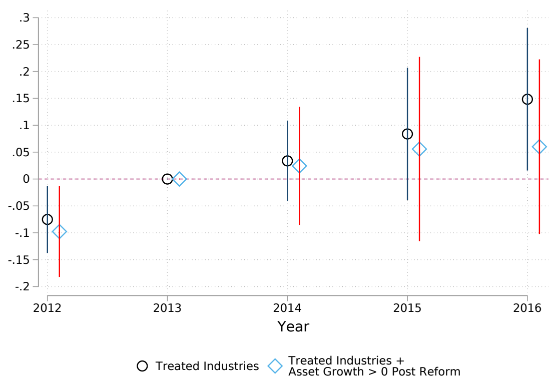
a **2014 Policy Change:** $Ln(K_t) - Ln(K_{t-1})$



b **2015 Policy Change:** $Ln(K_t) - Ln(K_{t-1})$



c **2014 Policy Change:** $Ln(K_t)$



d **2015 Policy Change:** $Ln(K_t)$

Note: This figure examines whether firms that claimed AD experienced differential increases in investment after the treatment. Defining C_i as a time-invariant indicator for whether the firm claimed AD in the post-implementation period (2014 - 2016 for the 2015 policy cohort, 2015 to 2016 for the 2015 cohort), we estimate the descriptive regression $y_{i,t} = \alpha_t + \alpha_i + \sum_{s \neq 0} \beta_s \times 1\{t = s\} \times C_i + \epsilon_{i,t,k}$ for the targeted industries. The figures plot estimates of β_s. The second series restricts the sample to firms that had at least one year of positive asset growth in the post-implementation period before estimating β_s. Standard errors are clustered at the three digit industry level.

Chapter 3

Understanding Social Insurance Participation in China

A major challenge for developing countries is the establishment of a universal social insurance (SI) system, including a broad and well-enforced contributory base. We study this challenge in the context of China's SI system. China's modern SI system for formal employees began in the 1990s, and consists of five insurance programs covering retirement, health, workplace injury, unemployment, and maternity. As of 2019, the largest of these programs, the Basic Old Age Insurance (BOAI), provided pension coverage to 435 million participants (312 million currently working, 123 million currently retired), with annual benefit outlays of 4.92 trillion RMB (760 billion USD) [Ministry of Human Resources and Social Security, 2019]. This system is funded through some of the highest payroll tax rates in the world, with the total rate reaching over 40% in many areas. Despite these high rates (or perhaps because of), in many areas of China SI is under-funded, with existing and projected deficits prompting interest in policy changes that would improve fiscal sustainability [Deng et al., 2021]. In this paper, we study a longstanding limitation of this system that affects both its fiscal health and the extent of its coverage: under-participation and non-compliance in the contributory base.

In the mid- to late-1990s, as China transitioned from a planned to a market economy, it adopted a mandatory "pay-as-you-go" pension system in which contributions from current workers helped to meet the retirement needs of workers who had earned low wages in the planned economy [Song et al., 2015]. In this initial redistributive design, SI funding would mainly come from employer contributions. As recently as 2016, the central government set the employer contribution rate for pension contributions (BOAI) at 20% of wages and at 8% for medical insurance (MI). All employer contributions go to the locally pooled SI fund instead of being credited to individual employee's accounts. Only employees' contributions—at 8% for pension and 2% for health SI—are recorded in notional individual accounts. Even these notional accounts are effectively pay-as-you-go since many jurisdictions draw from them to meet current expenditures [Fang and Feng, 2018]. In the aggregate, a tax of 38% was imposed on a worker's wage by these two types of SI alone. Unemployment and injury insurance increased the tax rate further.

Until now, progress in documenting even basic patterns about the contributory base has been hindered by data gaps. Early efforts to investigate firm compliance relied on a sample of just 5600 firm audits from a single city [Maitra et al., 2007; Nielsen and Smyth, 2008; Nyland et al., 2011]. Subsequent research turned to the National Bureau of Statistics (NBS) survey of industrial firms [Gao and Rickne, 2014, 2017; Rickne, 2013], but NBS data excludes small and medium-sized firms and all privately-owned service sector firms. We overcome these shortcomings by using unique taxpayer data from 900,000 firms in one large province to document new facts about the structure and determinants of the contributory base among all sizes and sectors. By comparison, 88% of firms (representing 65% of employees) in our data would be ineligible for inclusion in the NBS survey. Furthermore, the tax data benefits from China's very high degree of firm formality. Because most firms are registered with tax authorities, we are able to study the prevalence of labor formality (participating in SI) among otherwise formal firms, a distinction stressed by recent work [Ulyssea, 2018, 2020].

We start by documenting general patterns in non-compliance. First, we calculate that 54% of tax-registered firms, making up 24% of aggregate economic activity and 35% of employment, do not contribute into SI. This leaves many workers ineligible for future SI benefits and generates immediate revenue shortfalls for meeting current expenditure needs. Furthermore, among firms that do remit, we estimate that approximately 85% do not pay the legally mandated amount (under-compliant). Second, compliance increases sharply with firm size, such that SI participation among the largest firms is close to 80% but only 30% among the smallest.

Contributing to this gradient is the regressive structure of the SI payroll tax schedule. Because the SI schedule imposes a minimum SI contribution per employee, very low wage workers face average tax rates higher than the marginal statutory rate. In turn, since low-wage employment is far more prevalent among small firms, they face a greater incentive to evade. The same logic manifests across industries. Industries that rely on low-wage, low-skill labor are less compliant than high-skill, high-wage industries. The result is that the current employer-based SI system provides greater coverage to high income workers.

Next, we investigate how the highly decentralized nature of Chinese SI affects the base. China is unique in that premium and benefit obligations are often pooled at sub-provincial and even sub-prefectural levels ("pooling units"), even though contribution rates are set at the provincial (and prefectural) levels. Additionally, the local structure of SI administration creates *de facto* opportunities for local governments to determine the level of SI taxation [Frazier, 2010; Cui, 2011] in their areas. We first document striking variation in compliance across SI pooling units that cannot be accounted for by differences in firm composition. To narrow-in on one mechanism underlying this variation, we investigate whether budgetary pressures at the pooling unit level explain variation in compliance. In contrast, past literature has investigated variations in participation in response to statutory contribution rates [Mao et al., 2013]. However, statutory rates were increasingly homogeneous across cities by 2016, while the large geographic variation in compliance remained. This provides *prima facie* evidence of local governance driving participation differences rather than statutory rates.

To measure budgetary pressure at the pooling unit level, we collect official estimates of aggregate pension outlays for each pooling unit, and divide this by Census estimates of the total working age population (the potential tax base). We find that budgetary pressure strongly predicts both extensive and intensive margin compliance, consistent with the narrative that localities increase enforcement efforts when faced with more binding expenditure liabilities. Since the pension system is effectively pay-as-you-go, current obligations are mostly paid for by current premium collections. When the former rises, so must the latter. Consistent with an enforcement mechanism under-pinning this correlation, the effects of budgetary pressure on participation are highest in the middle of the firm size distribution, and non-existent in both the top and bottom deciles — small firms are not worth the enforcement effort and the largest firms are already quite compliant.

The extra enforcement-induced SI burden appears to be largely offset by reductions in other tax payments — for every dollar increase in SI remittance, combined tax payments across other taxes decline by 65 cents. This is consistent with two different views of the Chinese tax system. The first is that, like many emerging economies, tax compliance is far from perfect, and therefore when firms are induced to pay more of one tax, they increase their evasion efforts in other categories [Li et al., 2021]. The second explanation is that local authorities care not only about promoting tax compliance, but also promoting economic growth. As a result, when authorities increase the burden of SI contributions, they simultaneously reduce tax collections from other categories to offset the negative effects on economic activity. Consistent with both narratives, we find that the increased SI burden has a precisely estimated zero effect on firm output. We also find that the spillover effects of SI enforcement fall most strongly on those taxes for which the majority of revenue is retained locally, while there is no effect on taxes whose revenue goes entirely to the central government. This is congruous with evidence suggesting that tax competition between localities typically occurs in local taxes [Cui, 2011] where local authorities exercise greater *de facto* discretion.

Taken together, our results suggest that non-compliance in SI is not strictly the failure of resource-constrained tax authorities to fully enforce tax law. Rather local authorities tolerate some degree non-compliance subject to constraints on budgetary needs.

The remainder of the paper proceeds as follows. Section 3.1 outlines the institutional structure of Chinese SI and its highly decentralized nature and Section 4.2 describes the data advances in this paper. Section 3.3 provides general patterns of non-compliance across firms and Section 3.4 quantifies the degree of spatial variation in compliance. Section 3.5 explores the role of local governance and pooling unit budgetary pressures in driving variation in SI compliance. Section 3.6 concludes.

3.1 Institutional Background

While China's central government dictates a nationwide set of SI policies, sub-national governments are left to fund and operate SI systems.[42] As of 2020, only one province (Shaanxi) claimed to have a provincial pension SI system. Pension SI is organized at the prefectural (city) or lower, county level, in most of the country, and MI budgetary units may be even more decentralized. Despite very decentralized pooling, the central government has only authorized limited discretion to provinces to set contribution rates, which discretion some provinces often in turn grant to prefectural (but not lower) governments. In the province we study, the combined tax rate on wages was 40.7% on average in 2016.

SI obligations are determined on a monthly basis. The rate (τ) for each category is applied to employee i's monthly wage w_i to determine the liability for that employee. However, w_i is bounded above and below by $[.6\bar{w}_c, 3\bar{w}_c]$, where $\bar{w}_c$ is a statutorily chosen average monthly wage in city c, to create a minimum and maximum SI contribution per employee.[43] Panel A of Figure 3.1 illustrates this schedule. Panel B shows the derivation of marginal and average tax rates (MTR and ATR) for a given monthly wage, and the statutory rates in 2016 for each component.

Official statistics suggest that participants (workers) as a percentage of total urban employees was only 68.7% in 2017 (though this was already an increase from 45.1% in 2000) [Fang and Feng, 2018].[44] While this large compliance gap is no doubt attributable in part to high nominal contribution rates,[45] scholars have also conjectured that non-enforcement may be just as important a factor. Some argue that local officials are likely to limit enforcement, as this mitigates the adverse effect of SI collection on business formation and growth; a possibility that we investigate. Since all taxes may have potentially adverse effects on business formation and growth, the natural question is why local government agencies are particularly lax in enforcing SI relative to other taxes.

Another common conjecture is that Chinese provinces may designate either tax agencies or local social insurance administrations (SIAs) to collect SI contributions, and that the latter may be less capable of enforcement. However, we will show that participation is very low in the province we study, even though tax agencies had been responsible for collecting SI contributions well before 2016. Importantly, tax agencies merely collect—and do not actively assess—the SI liabilities already determined for firms by SIAs. Therefore, even if tax agencies have greater experience with enforcement against delinquent taxpayers and greater capacity for monitoring other aspects in the

[42] In recent years the central government increased the amounts of transfers that provinces with surpluses need to make to itself, which is in turn transferred to provinces with actual or imminent deficits. But the amounts of such transfers remain relatively small.

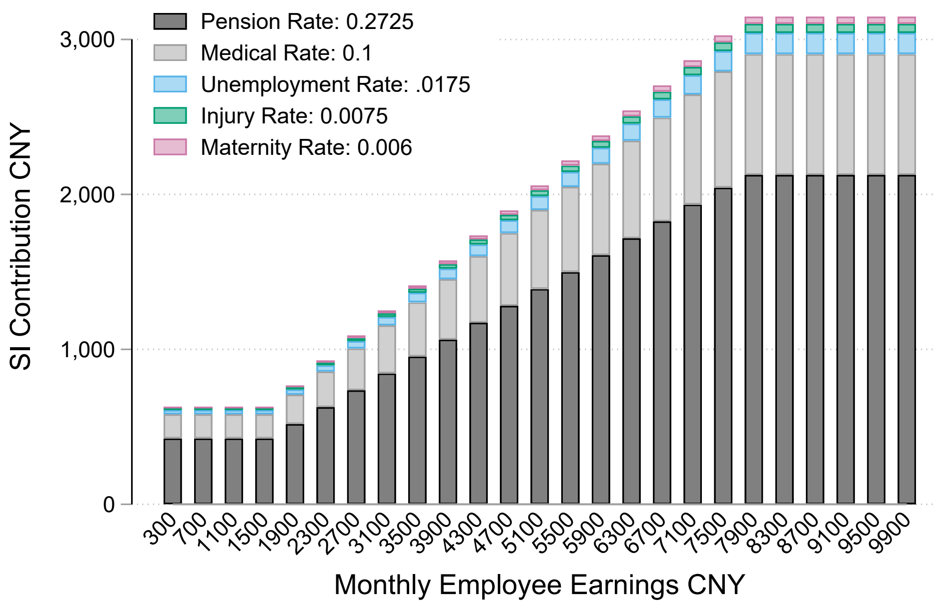
[43] The parameter w_c may not correspond to any measure of the actual average monthly wage.

[44] A government think-tank estimates that in 2015, 70% of all firms that participated in SI under-contributed relative to statutory requirements [Feng and Faqiang, 2019]. See also Tang and Feng [2019] for additional citations. Li et al. [2021] report a median effective contribution rate (SI payments over total firm wages) of only 0.9% in the NBS sample of firms they study.

[45] Feng [2013] provides evidence that for firms already participating in SI, lower tax rates may lead to incrementally greater compliance in terms of reducing under-contributions.

Figure 3.1: **The SI Contribution Schedule**

a **2016 Combined Employer and Employee Rates**



b **Marginal and Average Tax Rates**

	$w_i < .6\bar{w}_c$	$w_i \in [.6\bar{w}_c, 3\bar{w}_c]$	$w_i > 3\bar{w}_c$
MTR	0	τ	0
ATR	$\tau \times \frac{.6\bar{w}_c}{w}$	τ	$\tau \times \frac{3\bar{w}_c}{w}$

Category	$100 \times \tau_{2016}$
Pension	27.25
Unemployment	1.75
Injury (Inferred)	.755
Medical	10
Maternity	.6
Total	40.3

Note: Panel A illustrates the schedule for SI remittances for a fully compliant firm using 2016 rules. The tax base w_i is the monthly wage for employee i. The SI contribution statutorily required by the employer is the base multiplied by the combined (employee and employer portion) statutory rate τ. The taxable base is bounded below and above by $.6\bar{w}_c$ and $3\bar{w}_c$, where $\bar{w}_c$ approximates the average monthly wage in city c. Panel B illustrates implicit marginal and average payroll tax rates. The marginal payroll tax rate for an employee is the increase in SI contributions when the firm increases the employee's monthly wage by a dollar. The average payroll tax rate is the ratio of total SI contributions for an employee over that employee's monthly wage. Panel B shows the statutory rates in 2016 financial operations of firms, they would not be able to collect more SI than SIAs require firms to pay. The SIAs' decisions to assess SI liabilities, however, may reflect the budgetary health of each SI pooling unit: units that have high obligations for payouts relative to the contributory base may be more likely to assess SI liabilities against businesses. That is, enforcement efforts may depend on local fiscal preferences and pressures, instead of national requirements or enforcement capacity.

Two final considerations are worth noting. First, historically there were substantial barriers to portability of benefits across jurisdictions. Migrant workers making contributions in one region faced difficulties in accessing benefits when returning to their home region. For this reason, migrant workers and the firms who employ them are thought to have lower participation in SI. The extent to which portability frictions remain in 2016 is not well known, but even if the perception of frictions remains, so too will the incentive for migrants workers to remain outside of SI. Second, there is a parallel pension system for rural and self-employed residents: the Rural Resident Pension Scheme (RRPS) which was established between 2009 and 2013. While this system covers about as many individuals as the employed-based pension (BOAI), the former is less than 1/10th the size of the BOAI in expenditures due to substantially lower benefit levels. The population covered by the RRPS is intended to be persons that would not get coverage through the BOAI.

3.2 Data and Sample

3.2.1 Tax Return and Financial Statements:

We use an administrative data set from a large province in China containing financial records, tax returns, tax remittance, and tax registry information for the universe of firms in 2016.[46] This data provides three advantages for describing the nature of firm participation in SI. First, it contains all tax-registered firms, including those that do not make SI contributions. China is unusual in having a very high degree of tax registration such that most labor informality manifests at tax-registered firms, as opposed to labor hired by non-registered, informal firms.[47] As a result, we can offer a unique view of the varying degrees of SI participation across the entire firm-size distribution.

Second, the universal coverage and recency of the data provides significant advantages over existing literature. Existing research has relied on either on a survey of approximately 2100-5400 audited firms from Shanghai in 2001 and 2002 [Nyland et al., 2006; Maitra et al., 2007; Nielsen

[46]This data set was first used in Cui et al. [2020] to study tax preferences for investment in the corporate income tax. The current paper presents the first analysis of social insurance patterns.

[47]The combination of high firm formality and high labor informality in China is discussed in Chapter 3 of Cui [2021]. The China Taxation Yearbook (2002) reports outcomes for tax registration of newly established businesses in 2000 for the entire country, and across 31 provincial and 5 prefectural jurisdictions (pp 621-2, 627-8). The national average rate of registration for the State Tax Bureau (guoshui) system was 97% (out of 8.659 million firms and individual proprietors), while it was 95.7% for the Local Tax Bureau (dishui) system (out of 6.135 million firms and individual proprietors). While no similar national statistics has been published since then, internal reports within Chinese tax administration quote similar high rates of registration for more recent years.

and Smyth, 2008] or the NBS Survey of Industrial Firms for years 2001 to 2007 [Gao and Rickne, 2017; Rickne, 2013]. The latter contains all State-Owned Enterprises (SOEs) and private industrial firms above 5 million CNY ($800,000) in revenue. These criteria would exclude 88% of the firms (representing 65% of employees) in our data. Furthermore, the Chinese SI landscape has evolved considerably between 2001-2007 and 2016.

Table B.1 reports the number of tax-registered firms from this cross-section. We observe 1.4 million firms in the tax registry; 1.05 million of which filed non-empty financial returns; 922,000 of those reported positive revenue and costs on their financial return; and 893,402 of this last set had non-zero tax remittance (in any tax category). We take the 893,402 firms as our analysis sample under the intuition that firms without any tax remittance or revenue/costs are likely inactive entities.[48] We use and construct several variables from this data set:

Geography and Industry Classifiers: The tax registry provides detailed industry codes as recorded with the tax authorities, along with the geographic identifiers of the firm. Branches and subsidiaries are treated as separate tax registrants. In particular, we observe three units of geography: (a) prefectures which are large sub-provincial administrative divisions; (b) districts/counties which are sub-prefecture divisions closely corresponding to a city; and (c) neighborhoods which are divisions of districts. We use neighborhoods and districts quantify the variance in SI participation across areas in Section 3.4. We use district and prefecture identifiers to construct the SI pooling units used in Section 3.5.

Firm Inputs and Outputs: We use revenue and total assets as reported from financial statements throughout as a measure of firm output and size, respectively. Total wages paid for the tax year are reported on the corporate income tax (CIT) return which include SI contributions (which are CIT deductible). We calculate net-of-SI wage expenses by subtracting total SI remittances from the CIT wage bill. The number of employees is reported in the tax registry which we observe a snapshot of for 2017. This snapshot reflects the most recent time in which the firm's registration information was updated. Firms are prompted to update the information annually, although we do not observe the date of the most recent update, so the employee number may reflect employment from earlier years. Additionally, this point-in-time measure does not reflect turnover in the workforce throughout a given year. The measure of employees, therefore, is observed with error. Table 3.1 reports summary statistics for each of these variables.

Tax Remittances: We observe all tax remittances made throughout the tax year, net of any refunds. We collapse tax remittances into 5 general categories: SI contributions, value-added tax (VAT) and sales taxes, CIT, personal income tax (PIT, which are withheld by firms), and all other taxes.[49] Table 3.1 summarizes the share of firms' total tax revenue coming from each of these five

[48]Our data includes only taxpayers that are business entities and not individual proprietors (most of the latter would also be unlikely to participate in SI).

[49]Sales taxes include the Business Tax (*yingyeshui*) and excise taxes; the former was replaced by the VAT in 2016. Other taxes include deed and property taxes; land value, maintenance, and use taxes; resource tax; vehicle taxes;

categories. On average, SI contributions make up 21.4% of firms' total tax remittances, compared to 47% from VAT and Sales Taxes, 3.1% from the PIT, and 18.3% from the assortment of other taxes.

3.2.2 Census Data

Working Age Population: To measure the scale of the pooling-unit's potential tax base, we draw on estimates of the working age population living in each district from the 2010 Census. Since pooling-units are themselves districts, or groups of districts, we construct the working-age population in each pooling-unit by summing the working age population in its constituent districts. Working age is defined as age 15 to 65 in the Census aggregates, although retirement ages are 50 for women and 60 for men.

Migrant and Agricultural Populations: We draw upon two additional census population variables. The first is the combined population of inter-provincial and inter-prefectural migrants. The second is the population of residents with agricultural Hukou status (again from the 2010 census).

3.2.3 SI Outlays by Local Pooling Units:

We collected annual SI budgetary data from the published 2016 budgets of each prefecture (city) and each district/county in the province. Some urban districts do not have their own SI budgets because the city they are located in forms a pooling unit. But approximately half of the urban districts, as well as all of the counties, operated as independent pooling units with their own SI budgets. A typical SI budget reports several categories of revenue (e.g. contributions and government subsidies) and outlays (e.g. benefit payouts), as well as cumulative surpluses (deficits), for each of the several major types of SI (e.g. health and BOAI). In our analysis, we use observations of benefit payouts for BOAI, since it is the most consistently reported and accounts for the vast majority of total expenditures.

Table 3.1 shows descriptive statistics for these key budget and population measures. Average aggregate pension outlays (E) at the pooling-unit level are 9,002,870,000 CNY annually, or approximately 1.5 billion U.S. dollars. The average working age population (B) in a pooling-unit is 2.46 million persons. The average pension outlay per working age person (E/B) is 4226 CNY (704 U.S.). The mean annual earnings used for the purposes of defining the SI contribution limits, w_c, is approximately 68,000 CNY, implying that pension expenditures are equivalent to about 6 percent of average annual earnings of the working age population. In Section 3.5, we use this figure, the share of annual earnings of the working age population devoted to pension expenditures, as a local measure of budgetary pressure faced by SI administrators.

and stamp duty.

Table 3.1: **Descriptive Statistics**

	Mean	P25	P50	P75	P90	P95	N
Revenue(10000s)	1277	33	136	533	2101	5245	882768
Total Assets(10000s)	1769	52	163	587	2362	6715	882768
Employees	15	3	6	10	30	60	882762
Net of SI Wages(10000s)	79	0	9	37	153	370	882768
Mean Wage	91000	14000	35000	80000	190000	350000	616537
SI Taxes/Total Taxes	.214	0	0	.379	.744	.911	882768
VAT and Excise/Total Taxes	.47	.132	.511	.782	.886	.913	882768
CIT/Total Taxes	.1	0	.011	.101	.297	.567	882768
PIT/Total Taxes	.031	0	0	.012	.077	.166	882768
Other Taxes/Total Taxes	.183	.055	.094	.16	.518	1	882768
Pension Outlays (E)(10000s)	900409	176897	438109	999140	3018504	3018504	882768
Population 15 to 65 (B)	2464809	774834	1206550	4452086	4716990	9814744	882768
E over B	4226	1823	3084	6378	6399	7626	882768
Statutory Mean Wage	69000	67000	67000	73000	73000	73000	882768
E over (B x Mean Wage)	.06	.03	.04	.09	.1	.11	882768

Note: This table shows the means and percentile values, at the firm level, for key variables used throughout the paper. Pension Outlays are pooling-unit level aggregate outlays as of 2016. Population 15 to 65 is the the population between those ages in the pooling unit. Statutory Mean Wage is the statutorily defined local mean wage w_c (in CNY) used for the purposes of determining minimum and maximum SI contributions per employee, multiplied by 12, since w_c is defined as monthly earnings. In calculating the averages and percentile values of these pooling unit variables, we weight by the number of firms in each pooling unit.

3.3 General Patterns in SI Contributions and Participation

3.3.1 Margins of Noncompliance

Firms are legally required to report earnings for each of their employees, along with hew hires, on a monthly basis which local SIAs use to assess the SI obligations of a firm. The assessments are then passed to tax authorities who carry out collection. Several margins of under-payment can occur throughout this process.

First, firms can fail to register some or all of their employees with the SIA. In some cases, workers themselves may prefer this arrangement. In particular, migrant workers who face real or perceived barriers to the portability of SI benefits across SIA jurisdictional boundaries [Frazier, 2010; Mao et al., 2013; Gao and Rickne, 2017], low wage workers for whom the ATR is high, and workers who do not expect to accumulate 15 years of work in order to qualify for pension benefits[Gao and Rickne, 2017]. The obvious benefit to employees of this labor informality is higher net-of-tax wages. While estimates of economic incidence are limited in China, even a small share of the incidence is enough to generate non-trivial wage gains given the substantial statutory rates.[50]

[50] Nielsen and Smyth [2008] suggest that 18-33% of the incidence falls on workers in their sample of 2100 audited firms in Shanghai in 2001

Firms may also under-report the wages of participating employees with monthly earnings between $[.6w_c, 3w_c]$ where the marginal tax is positive. However, the incentive for employees to willingly collude is less clear. Future pension benefit levels are a function of the employee's average earnings[51], implying that under-reporting wages reduces pension benefits in retirement. From the employee's perspective, wage under-reporting therefore involves a trade-off between gains in net-of-tax wages today versus pension benefit levels during retirement. Regardless, firms may engage in wage under-reporting regardless of whether employees explicitly or tacitly consent.

Both wages and SI payments are deductible from the CIT base. This weakens under-reporting incentives under the assumption that firms under-report wages equally across both the CIT and SI tax bases (the results below partially validate this premise). As an example, a firm underreporting 100 in wages reduces SI obligations by $100 \times .4$, but increases its CIT liability by $100 \times 1.4 \times \tau$, where τ is CIT rate (assuming the firm is in a positive profit position). In net, a large firm with $\tau = .25$ only gains 5 $(40 - 35)$ from under-reporting. In contrast, a small or medium sized firm $(\tau = .1)$ gains 26 $(40 - 14)$. This generates a built-in incentive for higher non-compliance among small firms.

Finally, while the incentive structure of participation differs modestly across SI programs — Pension, MI, Injury, UI, Maternity — its unclear how a firm would manage to comply with some programs but not others. Indeed, in our data, 99.5% of firms that make positive contributions to a non-pension program also contribute to the pension program, and vice versa.

3.3.2 Measuring Compliance

We denote the extensive margin of participation in SI as whether the firm paid any SI. Panel A of Panel A of Figure 3.1 shows that only 46% of firms make SI contributions. These 46% of firms account for 76% of aggregate revenue, and 65% of employees. This leaves 54% of firms and 35% of employees outside the SI system.

We approximate intensive margin (IM) non-compliance among participating firms as:

$$\text{IM} = \frac{\text{Total SI}}{\text{Total Wages}} - ATR \tag{3.1}$$

The ATR is the best estimate of what $\frac{\text{Total SI}}{\text{Total Wages}}$ would be if the firm is fully compliant. Each firm's ATR is calculated by dividing its total wage bill by the number of employees, then dividing by twelve to calculate the monthly wage per employee (w) at the firm. The ATR is calculated by applying the formula for shown in Panel B of Figure 4.1) based on w. If the firm pays all their employees a wage between $.6w_c$ and $3w_c$, the difference $\frac{\text{Total SI}}{\text{Total Wages}} - ATR$ captures exact the gap in SI payments relative to legal obligations; a fully compliant firm would have IM equal to zero. This measure is subject to caveats. First, if the firm pays some employees wages outside of $.6w_c$

[51] The benefit formula leads to replacement rates of between 40% and 60%

and $3w_c$, then IM is only an approximate compliance measure. Second, equation (3.1) relies on the number of employees listed in the tax registry, which likely measures with error the number of persons employed with the firm during the year. Third, wage expenses reported for CIT may mis-measure the the taxable salary for the purposes of SI.

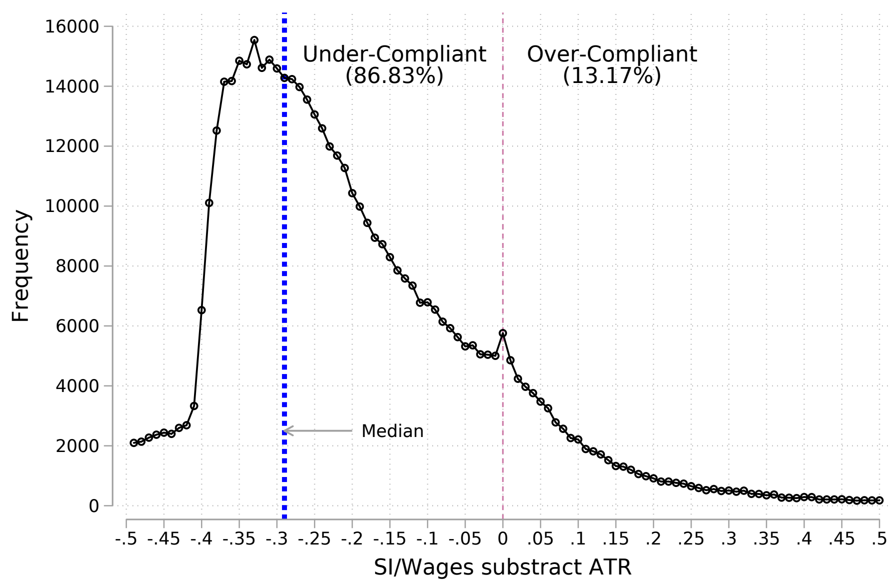
Subject to these caveats, Panel B of Figure 3.2 plots the distribution of IM (among participating firms). The zero line denotes firms with SI contributions exactly equal to ATR. Firms to the left of zero are under-compliant (86.83%) and firms to the right are over-compliant (13.17%). To put these in perspective, in the 2001 audit of 2,200 Shanghai firms, 71% were found to be under-compliant, 4.7% paid the prescribed amount, and 24.3% overpaid. Similarly, a government think-tank estimates that in 2015, 70% of all firms that participated in SI under-contributed relative to statutory requirements [Feng and Faqiang, 2019].

Figure 3.2: **Measures of Compliance**

a **Extensive Margin**

% of Firms Contributing to SI	46.48
% of Total Employees at Participating Firms	65.88
% of Total Revenue at Participating Firms	75.2

b **Intensive Margin**



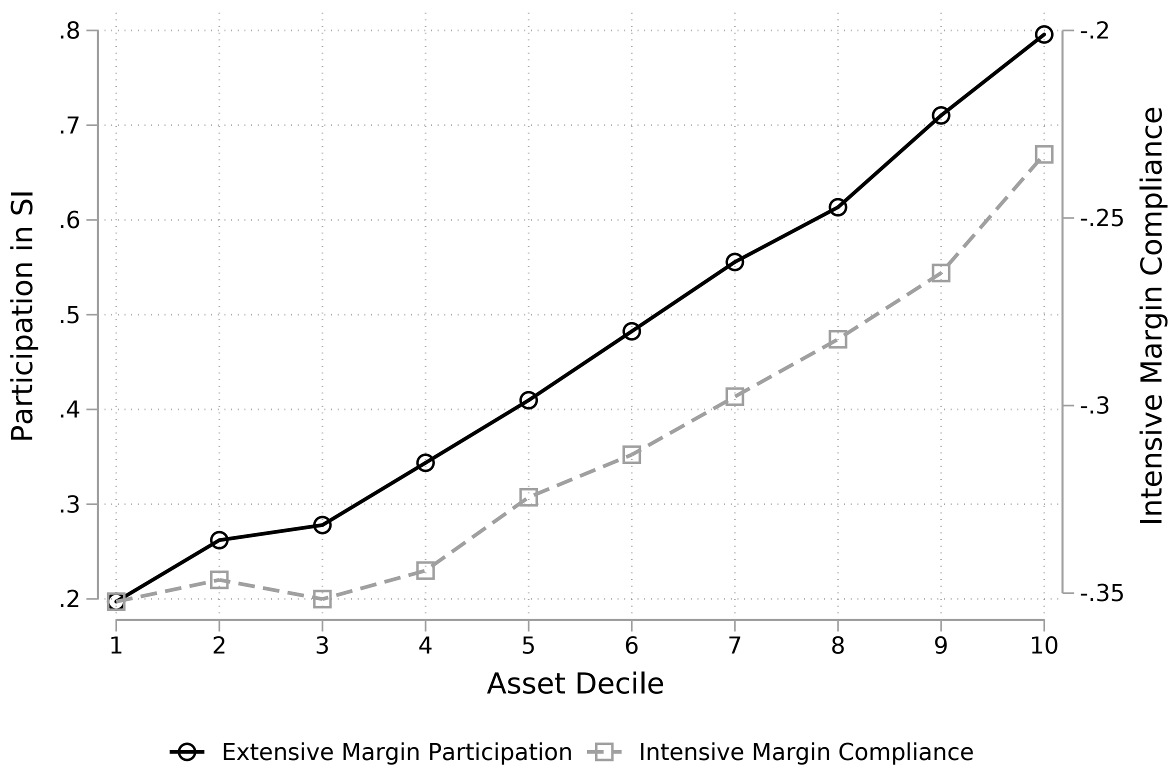
Note: Panel A shows the fraction of firms that made contributions to SI; the fraction of the aggregate number of employees in the sample that are employed at SI participating firms; and the fraction of total output accounted for by participating firms. Panel B plots the distribution of intensive margin compliance, defined as $\frac{\text{Total SI Payments}}{\text{Total Firm Wage Bill}}$ subtract the ATR that prevails at the firm's average wage (total wages over total employees). Firms to the left of zero are considered to be under-compliant, subject to the caveats discussed in text.

3.3.3 Firm Determinants of Compliance

We begin by characterizing the size gradient of extensive margin firm participation in SI in Figure 3.3. We split firms in ten deciles based on their total asset stock, then plot the the average participation rate in each decile, and among participating firms, the median intensive margin compliance. SI participation is only 20% among the smallest firms and gradually rises to 80% among the largest. Likewise, intensive margin compliance increases substantially with firm size.

Two complementary explanations exist for the size narrative. First, constrained tax administrators are unlikely to bother with enforcing SI payments among the large swathe of small firms given the low revenue gains of such enforcement (Frazier [2010] reports anecdotal accounts of this phenomenon in the 2000s). Second, small firms often pay lower wages, which implies higher ATRs on employment due to the regressive SI schedule, which in turn encourages greater non-compliance.

Figure 3.3: **Compliance Across the Firm Size Distribution**



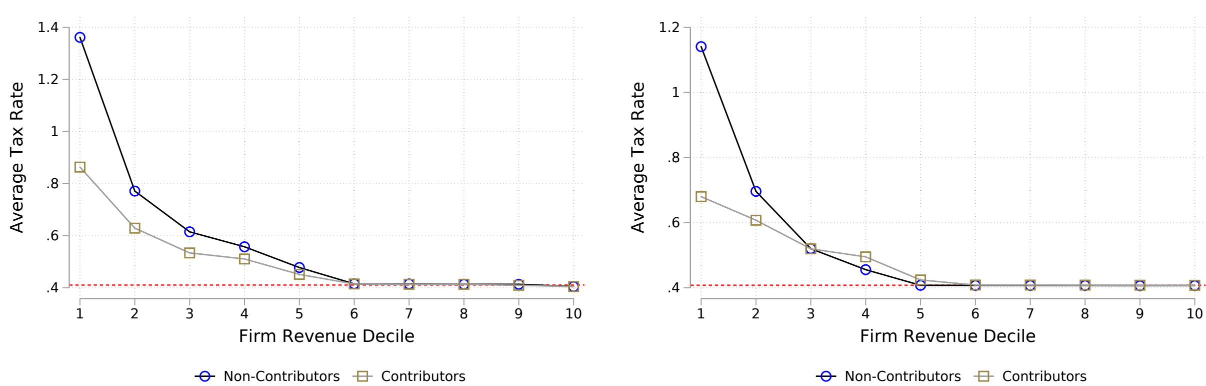
Note: For each firm size (revenue) decile, the black series plots the fraction of firms that remitted SI contributions in 2016 in each firm revenue decile. Approximately 46% of active firms remitted SI contributions. Only 22% of the smallest decile participate, while 78% of the largest decile do. The grey series plots the fraction of firms within each decile that remitted SI contributions out of a restricted sample of firms that reported more than CNY 100,000 in wages on their corporate income tax returns. The dashed magenta series plots the fraction of aggregate SI remittance that was made by each firm decile.

To explore this second mechanism, Panel A of Figure 3.4a plots the median ATR in each decile separately for SI contributing firms and non-contributing firms (calculating of ATRs is described in section 3.3.2). Two facts are apparent. First, the ATR is is substantially larger than the statutory rate (τ) for the bottom half of the firm distribution. Second, among the bottom half, SI contributing firms have much lower ATRs implying that firms select into SI participation based on the effective SI burden they face, and that part of the labor informality gradient is driven by higher ATRs among smaller firms.

Dividing total wages by the number of employees results in a downward bias of average wage when employees are mis-measured, and therefore an upward bias in the ATR. As a check on this division bias, Panel B instead calculates ATRs in each group based on that group's aggregate wage. We define the aggregate wage bill for group g as $\sum_{i \in g} W_i$ divided by $\sum_{i \in g} E_i$, where W_i and E_i denote firm i's annual wage bill and total employees, respectively. By summing within the denominator and numerator, mean-zero measurement error collapses to zero. The trade-off is that the aggregate mean wage is overly influenced by the largest firms in a group (high W and E), which re more likely to pay higher wages, which will also lower the estimated ATR. Consistent with both, Panel B shows that calculating ATRs with this alternative approach reduces the ATRs. Nonetheless, the smallest three deciles still exhibit ATRs greater than the statutory rate, and firms still appear to select into participation according to their ATR.

Figure 3.4: **Average Tax Rates (ATR)**

a **Median Firm-Level ATR** b **ATR at the Aggregate Decile Wage**



Note: Panel A plots the average tax rate (ATR) for each asset decile as follows: (1) Asset deciles are calculated for the full sample. (2) Each decile is split into SI contributing and non-contributing firms, creating 10 × 2 bins. (3) For firm i, its average wage w_i is calculated as its total annual wage bill divided by the total number of employees, then further divided by 12. (4) The ATR is then calculated for each firm following the formula shown in Figure 4.1. (5) The median ATR is then plotted for each bin. The red horizontal line demarcates the combined statutory rate across all contribution categories in 2016. If $w_i \in [.6\bar{w}_c, 3\bar{w}_c]$, the ATR is equal the statutory rate. In Panel B, an average wage is constructed for each group by dividing the sum of wages in the group by the sum of employees, then calculating the ATR based on that average wage.

As further descriptive evidence for ATRs influencing compliance, Panels A and B of Figure 3.5 correlate industry level compliance with two-digit industry average wages (and therefore negatively correlated with ATRs). Both extensive and intensive margin compliance increase with the average wage paid by an industry. Interpreting the slopes, a 10% increase in wages increases SI participation by 1.5 percentage points (p.p) and increases the median IM by .018. The effect on IM is in essence a 1.8 p.p. the increase in the effective SI tax rate.

Of course, high-wage industries correspond to high-education and high-skill industries. These industries are likely to have more stable employment and employ workers who have a greater incentive to participate. Panel C shows average compliance across 18 aggregated industry codes which corroborates this at first glance. The least compliant industries include agriculture, forestry, and fisheries; transportation; wholesale and retail; mining; and entertainment. In contrast, the most compliant firms include education and health services, financial and business services, and high tech industries. Panel C also shows the share of workers in each industry that have greater than post-secondary education.[52] The most compliant industries tend to employ the highest educated workforce. As a result, SI coverage is skewed towards high-income, high-skilled workers.

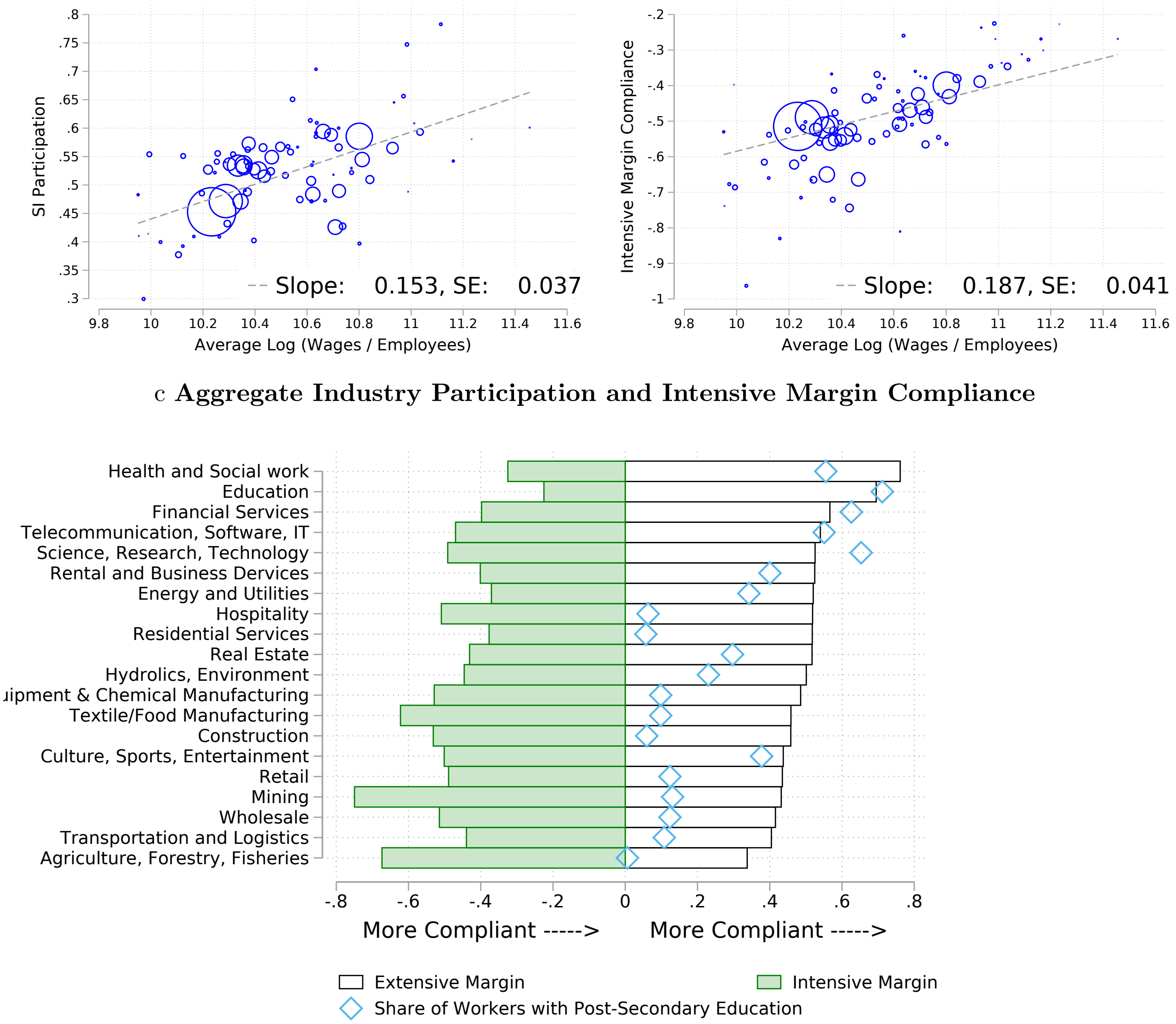
[52]Obtained from nationwide 2010 Census information.

Figure 3.5: **Compliance by Industry**

a **Intensive Margin and Average Wages**

b **Extensive Margin and Average Wages**

c **Aggregate Industry Participation and Intensive Margin Compliance**



Note: This figure illustrates compliance patterns across industries. At the firm level, we regress log(wages/employees), extensive margin compliance, and intensive margin compliance on fixed effects for age, ownership type, urban vs rural, and fifty equal-frequency asset bins (to account for firm size). We then average the residuals at the two-digit industry level and plot the correlations in Panels A and B. In Panel A, the y-axis in panel A is the fraction of firms in the industry that contribute SI. The y-axis in panel B is the median intensive margin (IM) compliance within the industry. The slope is the size-weighted regression line of the industry-level variables. Panel C plots average compliance in each aggregated industry category, after controlling for the same covariates from Panels A and B. Panel C also plots the share of each industry's workforce that has post-secondary education. These are nationwide aggregates obtained from the 2010 Census.

3.4 Regional Variation

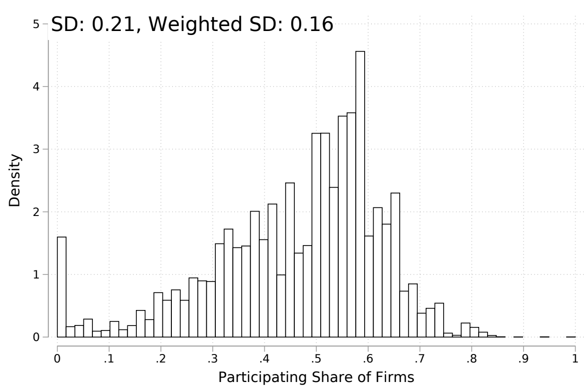
This section documents substantial variation in compliance across regions, a sizeable share of which cannot be accounted for by differences in firm composition. This fact motivates the subsequent analysis in Section 3.5 which investigates how the devolution of responsibility to local governments drives variation in compliance.

We focus in particular on neighborhood-level rates of compliance. Neighborhoods represent granular divisions of districts and are the lowest level of geography available in the data. SI pooling units, in turn, are combinations of districts. On average there are 43 neighborhoods per pooling unit and 550 firms per neighborhood. Neighborhoods are therefore large enough to measure average levels of compliance in an area without substantial noise, but narrow enough to examine whether compliance varies across areas.

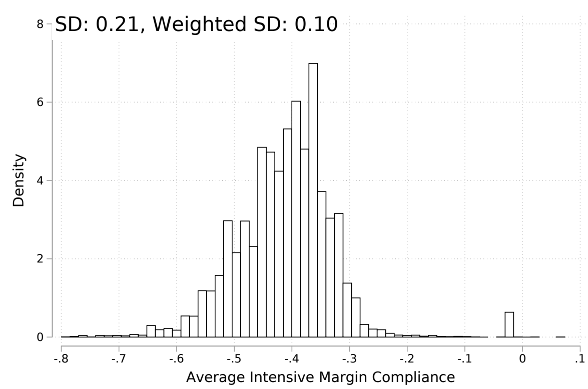
Figure 3.6 starts by plotting the distributions of neighborhood level compliance, weighted by the number of firms in each area. Panel A plots SI participation rates while panel B plots average intensive margin compliance. There is substantial variation across neighborhoods. The standard deviation of participation rates is .16 (16 percentage points), and the standard deviation of intensive margin compliance is .1 – which corresponds to a 10 p.p change in the effective tax rate on wages. To put this in perspective, the standard deviation in neighborhood-level IM is equivalent to the gap between the bottom decile and top decile of firms in Figure 3.3.

Figure 3.6: **Distribution of Neighborhood Level Compliance**

a **Extensive Margin Distribution**



b **Intensive Margin Distribution**



Note: The bars plot the histogram of neighborhood-level participation rates and average intensive margin compliance, each weighted by the number of firms in the neighborhood.

Table 3.2 goes further by decomposing the variance in neighborhood compliance into the variance accounted for by firm characteristics, by pooling-unit (d) fixed effects, and neighborhood-level unobservables by estimating the following fixed effects model:

$$p_n = X_n' \beta + \gamma_{d(n)} + \varepsilon_n \tag{3.2}$$

where p_n is neighborhood average compliance, X_n contains average traits of firms in neighborhood n and γ_d is a pooling unit fixed effect. In estimating equation (3.2), we weight each neighborhood by the number of firms in it (n_f) to obtain size-adjusted estimates of γ_d and β. Our measure of the share of variance accounted for by pooling-unit factors is $Var(\gamma_d)/Var(p_n)$. We estimate the numerator by plugging in the estimated fixed effects: $Var(\hat{\gamma}_d) = \sum_{d=1}^{D} \frac{n_d}{N}(\hat{\gamma}_d - \sum_{d=1}^{D} \frac{n_d}{N}\hat{\gamma}_d)^2$ where n_d is the number of firms in district d and N the total number of firms in the province.

Table 3.2: **Geographic Dispersion of Neighborhood Compliance**

	Extensive Margin Participation			Intensive Margin Compliance		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Mean Revenue)		0.035***	0.035***		0.018***	0.011***
		(0.005)	(0.010)		(0.003)	(0.003)
Ln(Mean Firm Age)		0.276***	0.292***		0.006	0.039***
		(0.041)	(0.018)		(0.017)	(0.015)
Fraction State-Owned		-0.426**	-0.477**		0.081	-0.041
		(0.203)	(0.216)		(0.160)	(0.158)
Fraction Foreign-Owned		-0.825	-1.012		0.206***	0.180***
		(0.943)	(0.859)		(0.046)	(0.050)
Fraction HMT-Owned		0.186	0.090		0.126	0.377**
		(0.554)	(0.646)		(0.165)	(0.147)
Industry Controls			✓			✓
No obs (neighborhoods)	1619	1619	1619	1568	1568	1568
Approx. No Pooling Units	70	70	70	70	70	70
$Var(\hat{\delta}_d)/Var(p_n)$	0.537	0.445	0.467	0.267	0.261	0.202
$Var(\hat{\varepsilon}_n)/Var(p_n)$	0.463	0.358	0.345	0.315	0.278	0.257
SD(p_n)	0.164	0.164	0.164	0.096	0.096	0.096

Note: This table presents estimates from equation (3.2) along with estimates of $Var(\gamma_d)/Var(p_n)$ and $Var(\hat{\epsilon}_n)/Var(p_n)$. Standard errors for the coefficients β (from equation (3.2)) are in parentheses and clustered at the district level. $*p < .1$, $**p < .05$, $***p < .01$

Columns (1) through (3) examine extensive margin compliance with sequentially more controls X. In column (1), without controls, the share of participation rate variance accounted for by pooling units is 0.54; the remaining 0.46 is attributed to within-pooling-unit variance. Column (2) introduces controls for the logarithm of mean firm revenue, mean firm age, and the fraction of firms under different ownership types — state-owned, foreign-owned, or Hong Kong, Macau or Taiwan-owned (the base group is private domestic firms). Column (3) further controls for the fraction of firms in each of twenty industry groups. Taking column (3), the share of variance accounted for by pooling-unit-level factors is .467, substantially larger than the .34 which is attributable to neighborhood-level unobservables, suggesting something drives participation differences across pooling-units. Columns (4) through (5) do the same exercise for intensive margin compliance. In column (6), 20 percent of the variation in IM is accounted for by pooling-unit variation.

3.5 Does Decentralization Drive SI Compliance?

China's SI system is unique in that SI premiums and liabilities are pooled at sub-provincial, and often sub-prefectural, levels (such as a district), in contrast to many countries which pool insurance risk at provincial or national levels. This granular level of risk pooling creates substantial geographic variation in budgetary pressures. The enforcement and collection of SI premiums is similarly fragmented, reflecting China's highly decentralized method of tax enforcement and collection [Cui, 2015]. These two facts combine to generate the hypothesis that the substantial variation across space is, at least partially, driven by enforcement efforts that respond endogenously to budgetary needs. This hypothesis is consistent with anecdotal accounts of the incentives and practices of local SI authorities documented by Frazier [2010].

We test this hypothesis by drawing on the total pension outlays from the BOAI (E_j) data described in Section 3.2.3. We divide these by the product of the total working age population (B_j) representing an estimate of the total potential contributory base. We refer to this ratio as *budgetary pressure*: $P_j = \frac{E_j}{B_j}$. Budgetary pressure captures the amount of the amount of SI revenue per working age person required to meet current aggregate expenditure. The higher is P_j, the greater the need for local authorities to collect more SI contributions from the working population. To estimate the effect of P_j on SI participation, we estimate the following at the firm level:

$$y_{i,j} = \beta \ln(P_j) + \gamma X_{i,j} + \epsilon_i \tag{3.3}$$

where $X_{i,j}$ are firm and pooling-unit characteristics. In Panel A of Table 3.3, the outcome is $\mathbb{1}\{SI_i > 0\}$, the extensive margin of firm participation in SI. The coefficients β therefore represent the increase in the share of firms that are SI participants corresponding to a 100% increase in budgetary pressure. For example, column (1) tells us that a doubling of budgetary pressure is expected to increase the share of firms that are SI participants by 3.8 percentage points. Put differently, the inter-quartile range of $\ln(P_j)$ is 1.1, and therefore moving from the 25th to 75th percentile of budgetary pressure is associated with a 4.18 (1.1×3.8) percentage point increase in SI participation (see Table 4.1 for the inter-quartile ranges).

Subsequent columns of Table 3.3 show that this effect is resilient to potential confounders. One concern is that a pooling unit's level of budgetary pressure may be correlated with the types of firms it contains. Column (2) addresses this by including fixed effects for firm-level traits: four-digit industry (approximately 1000 industries), 50 equal-frequency firm asset bins, firm age, and ownership

Table 3.3: **Correlation Between Firm-Level SI and Pooling Unit Budgetary Pressure**

Panel A	SI Contributions > 0				Wages > 0
	(1)	(2)	(3)	(4)	(5)
Ln(Budgetary Pressure)	0.038**	0.036***	0.026**	0.033***	0.021***
	(0.016)	(0.012)	(0.011)	(0.010)	(0.006)
Urban District			0.034	0.027	0.004
			(0.032)	(0.024)	(0.017)
Agricultural Pop. Share			-0.056*	-0.044**	-0.038***
			(0.030)	(0.020)	(0.009)
Migrant Share			0.344***	0.267***	0.101***
			(0.089)	(0.086)	(0.033)
Outcome Mean	0.466	0.466	0.463	0.463	0.702
Number of firms	834679	834651	820461	820461	820461
Firm Size Decile FEs		✓	✓	✓	✓
Firm Age FEs		✓	✓	✓	✓
Industry and Owner-Type FEs		✓	✓	✓	✓
Prefecture FEs				✓	✓

	Intensive Margin Compliance				Ln(Mean Wage)
	(1)	(2)	(3)	(4)	(5)
Ln(Budgetary Pressure)	0.015**	0.019**	0.023***	0.016*	-0.001
	(0.008)	(0.009)	(0.008)	(0.009)	(0.029)
Urban District			-0.012	-0.011	-0.025
			(0.022)	(0.015)	(0.061)
Agricultural Pop. Share			-0.069***	-0.030***	-0.009
			(0.017)	(0.007)	(0.045)
Migrant Share			0.135***	0.299***	0.773***
			(0.035)	(0.042)	(0.246)
Outcome Mean	-0.405	-0.405	-0.406	-0.406	1.000
Number of firms	298096	298049	290473	290473	283843
Firm Size Decile FEs		✓	✓	✓	✓
Firm Age FEs		✓	✓	✓	✓
Industry and Owner-Type FEs		✓	✓	✓	✓
Prefecture FEs				✓	✓

Note: Columns (1) through (5) show estimates of the effect of budgetary pressure on SI participation (from equation (3.3)). In Panel A the outcome is a firm-level indicator for remitting any SI contributions. In Panel B, it is total SI contributions over firm revenue. Column (6) shows analogous estimates using reported wages instead of SI payments. Coefficients in Panel B are scaled by 100. Standard errors are reported in parentheses and clustered at the pooling unit level. $^*p < .1$, $^{**}p < .05$, $^{***}p < .01$.

type. Another type of concern is that budgetary pressure is correlated with other geographically defined determinants of participation, such as urbanization and prefecture-level policy. Column (3) adds an indicator for whether the district is urban or rural, the share of the population that is administratively classified as agricultural, and the share of the population that are migrants. Column (4) further includes prefecture fixed effects.[53] Interpreting column (4), moving from the 25th to the 75th percentile of budgetary pressure increases SI participation by 3.63 (1.1×3.3) p.p.. Panel A of Figure 3.7 plots the variation underlying column (4).[54]

The last column of Table 3.3 shows that increases in budgetary pressure are not just associated with SI participation, but also with reporting positive wages on a firm's corporate tax return. The outcome is an indicator for reporting positive wages. The magnitude of the estimate suggests that of the firms that are induced to participate in SI due to the additional enforcement caused by budgetary pressure, 63% (2.1/3.3) start to report positive wages when they otherwise would not have. This is consistent with the idea that extensive margin SI avoidance is associated with non-reporting of wages on corporate tax returns.

The second panel shows the same exercise for intensive margin compliance. As with the extensive margin, areas with higher SI budgetary pressure have higher intensive margin compliance. Column (4) indicates that moving from the 25th to 75th percentile of budgetary pressure corresponds to a .0176 ($1.1 \times .016$) increase in intensive margin compliance — a 1.76 p.p increase in the effective tax on wages. Panel B of Figure 3.7 plots the variation underlying column (4).

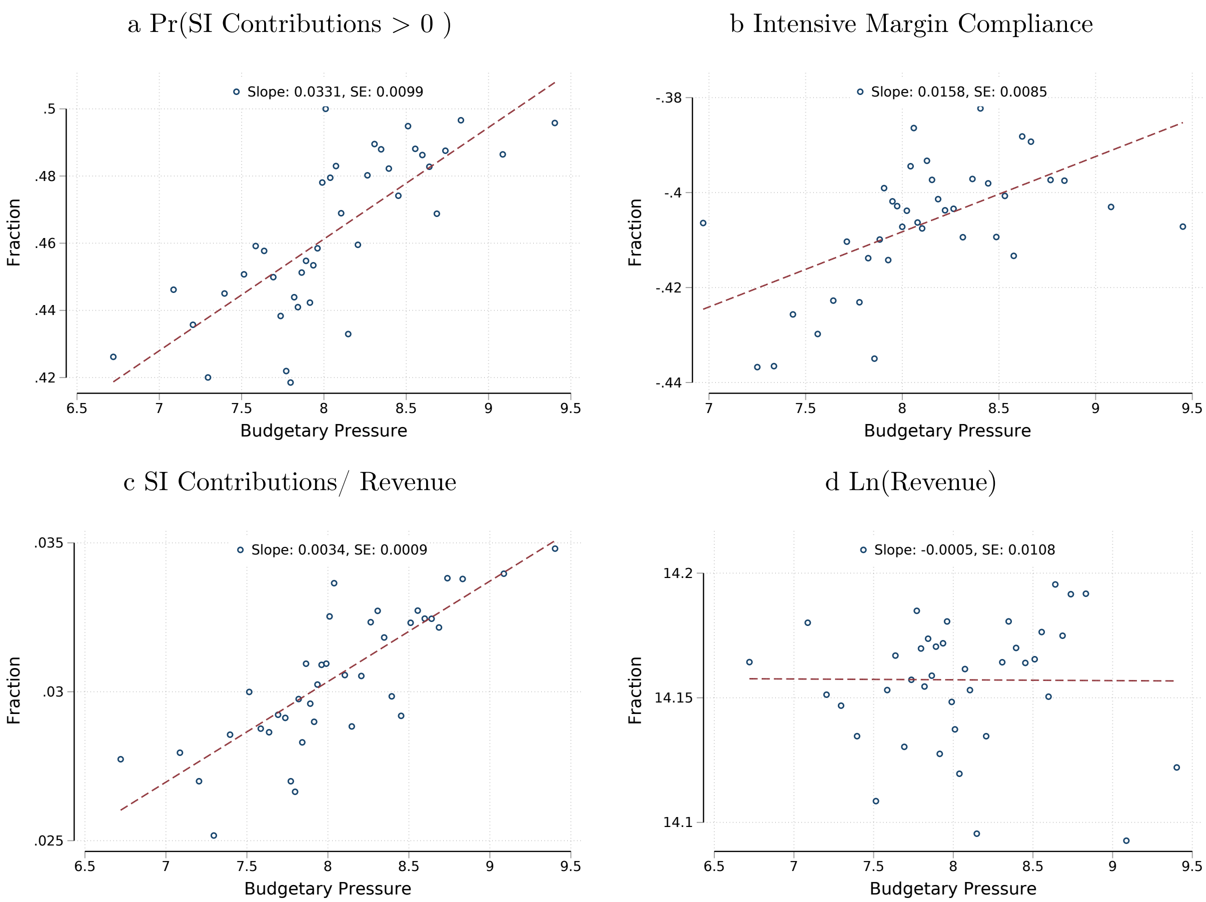
To capture the effect on total SI revenue column (1) of Table 3.4 reports estimates of equation (3.3) where the dependent variable is $SI_i/\text{Revenue}_i$. This measure captures the combined effect on per-firm SI burdens resulting from all margins. Reported coefficients and outcome means are scaled up by 100. Column (1) indicates that doubling of budgetary pressure increases the fraction of revenue going towards SI payments by .337 p.p; on a base of 3.051 p.p., this is a 11% increase in SI payments as a share of revenue (Panel B of Figure 3.7 illustrates this variation).

Subsequent columns of Table 3.4 considers spillover effects of SI budgetary pressure onto other categories of tax payments. This serves two purposes. One the one hand, the enforcement effect of SI budget pressures is not expected to affect other types of tax remittances directly, since revenue from these categories does not fund local SI outlays. And therefore other tax categories may serve as a useful placebo check on the unconfoundedness of P_j. On the other hand, firms that are induced to pay more SI remittances may (a) try to lower other tax payments through avoidance or evasion and (b) naturally pay fewer taxes if the additional SI burden reduces economic activity (and therefore the tax bases of CIT and VAT). CIT is especially likely to experience spillover effects because reported wages, a deduction from the CIT base, rise as a byproduct of the increased SI enforcement (as in

[53]Column (4) therefore effectively ignores prefectures without sub-prefectural pooling-units in identifying the effect of budgetary pressure.

[54]Table B.2 shows that the effect of budgetary pressure — which is based on *pension* budget pressures — has very similar effects for participation in all non-pension SI programs, consistent with firms either contributing to all programs or to none.

Figure 3.7: **Binned Correlation Between SI Participation and Pooling Unit Budgetary Pressure**



Note: This figure visualizes column (5) of Table 3.3. Both the outcome and the budgetary pressure variables are regressed on the remaining set of control variables. The average residuals are plotted above in 40 equal-frequency bins. The slope of the fitted line is equal to the coefficient in column (4) of Table 3.3.

column (5) of Table 3.3).

Table 3.4: **Spillovers to Other Tax Categories**

	SI / Revenue (1)	CIT / Revenue (2)	Sales Taxes / Revenue (3)	Other Taxes / Revenue (4)	All Non-SI Taxes / Revenue (5)
Ln(Budgetary Pressure)	0.337***	-0.032***	-0.087***	-0.066**	-0.217***
	(0.087)	(0.007)	(0.031)	(0.027)	(0.059)
Agricultural Pop. Share	-0.672***	0.007	0.197***	0.156***	0.381***
	(0.195)	(0.010)	(0.067)	(0.035)	(0.101)
Migrant Share	2.844***	-0.149***	0.159	-0.248	-0.171
	(0.682)	(0.049)	(0.264)	(0.167)	(0.411)
Urban District	0.042	0.033	-0.160*	0.067	-0.049
	(0.142)	(0.023)	(0.089)	(0.059)	(0.174)
Outcome Mean	3.051	0.389	2.702	1.071	4.790
Elasticity	0.110	-0.082	-0.032	-0.062	-0.045
Number of firms	820461	820461	820461	820461	820461
Firm Size Decile FEs	✓	✓	✓	✓	✓
Firm Age FEs	✓	✓	✓	✓	✓
Industry and Owner-Type FEs	✓	✓	✓	✓	✓
Prefecture FEs	✓	✓	✓	✓	✓

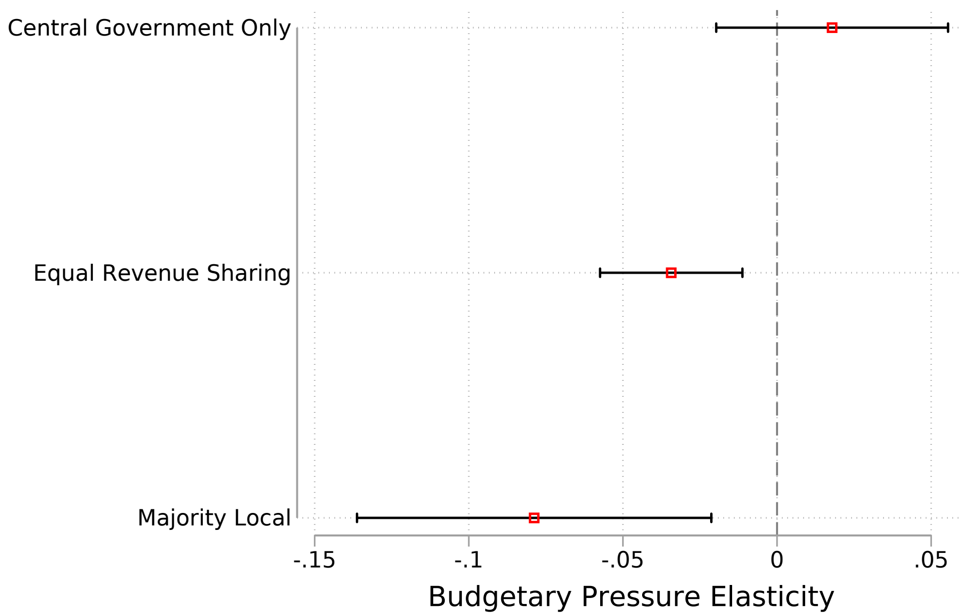
Note: In the first three columns, the outcome is total tax remittances of the specified tax type divided by firm revenue. In the fourth column, the outcome is wages reported in the corporate income tax return divided by firm revenue. The coefficients and the displayed outcome mean are multiplied by 100. Standard errors in parentheses clustered at the pooling unit level. *$p < .1$, **$p < .05$, ***$p < .01$.

Column (2) indeed reports a negative effect of SI budget pressure on CIT payments, about 1/10th the size of the effect on SI remittances. Column (3) reports a negative effect on VAT remittance approximately 1/4th the magnitude of the SI effect. Column (4) reports reductions in other tax payments similar in magnitude to the effect on CIT payments. The combined spillover effect across all non-SI taxes in column (5) shows that the reduction in non-SI taxes almost perfectly offsets the increase in SI tax payments.

Taking stock, the results suggest two potentially complementary stories. The first is that, like many emerging economies, tax compliance as far from perfect, and therefore when firms are induced to pay more of one tax, they increase their evasion efforts in other categories [Li et al., 2021]. The second explanation is that local authorities care not only about promoting tax compliance, but also promoting economic growth. As a result, when authorities increase the burden of SI contributions, they simultaneously reduce tax collections from other categories to offset the negative effects on economic activity. Consistent with both narratives, panel D of Figure 3.7 shows that budgetary pressure has a precisely estimated zero effect on firm output.

Figure 3.8 re-groups the non-SI taxes into three types: taxes whose revenue goes entirely to the central government (excise taxes); taxes whose revenue is equally split between national and sub-national governments (VAT); and taxes whose revenue is majority-retained in the sub-national jurisdictions. As in Table 3.4, we estimate β from equation (3.3) with the outcome being tax payments in each group normalized by firm revenue. Figure 3.8 reports the elasticities — β/Outcome Mean — for each tax group. The spillover elasticity of SI enforcement fall is highest for taxes in which the majority of revenue is retained locally, while there is no effect on taxes whose revenue goes entirely to the central government. This is congruous with evidence suggesting that tax competition between localities typically occurs in local taxes [Cui, 2011], where local governments ostensibly have more discretion, and consequently, suggests that tax authorities partially allow compensatory reductions in non-SI taxes.

Figure 3.8: **Elasticities of Tax Revenue with Respect to Budgetary Pressure**



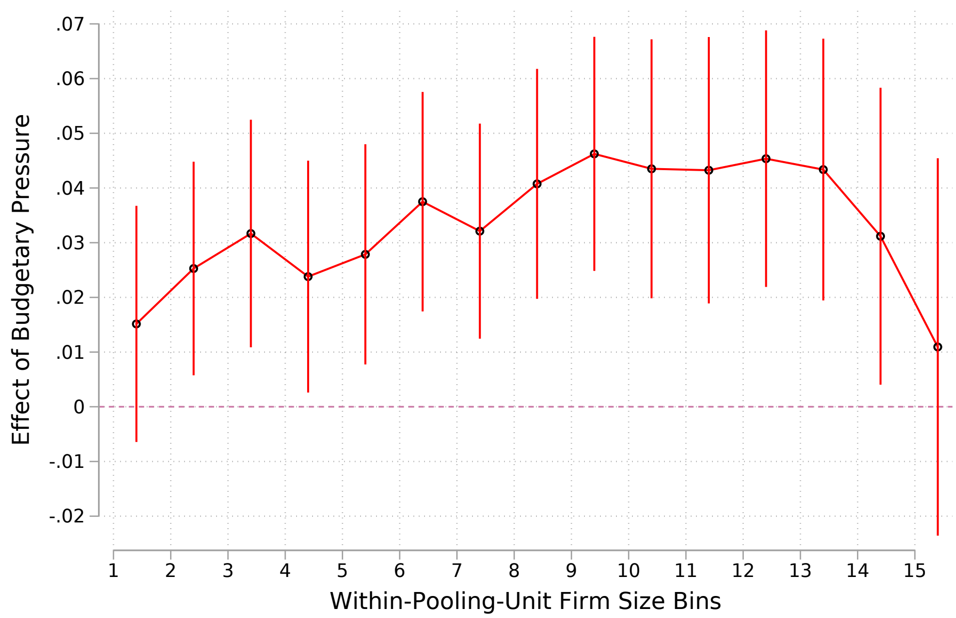
Note: This figure plots estimates of β from equation (3.3) divided by the outcome mean, thereby representing an elasticity, and 95% confidence intervals. The outcome is firm tax remittances over firm revenue for three categories of taxes: those whose tax revenue goes entirely to the central government, those whose revenue is equally split between national and sub-national governments, and those where the majority of revenue is retained at the prefectural level.

We next consider how the enforcement effects fall across the firm size distribution. In the constrained-enforcement story, tax administers have to decide how to allocate scarce enforcement resources. Naturally, the largest firms contain the most lucrative tax bases, and therefore offer the best opportunity for SI revenues. However, to the extent that participation is already highest among the largest firms, the effects of additional enforcement on the margin may land in the middle of the distribution. The effort required to enforce SI participation among small businesses is unlikely to justify the revenue gains. To test this hypothesis, we construct 15 within-pooling unit bins (b) of firm size (as opposed to province-wide rankings). We then interact $Ln(P_j)$ in equation (3.3) with indicators for each bin:

$$y_{i,j} = \sum_b \beta_b \ln(P_j) + \gamma X_{i,j} + \epsilon_i \tag{3.4}$$

Figure 3.9 plots the estimates of β_b on extensive margin participation. Consistent with the explanation proposed above, the marginal effect of budgetary pressure is indistinguishable from zero among the smallest firms, highest amongst the upper-middle deciles, and zero in the largest decile.

Figure 3.9: **The Effect of Budgetary Pressure on SI Participation by Firm Size**



Note: This figure plots estimates β_b from equation (3.4) representing the effect of pressure on SI participation in each of 15 firm sized bins. The solid blue series does not include prefecture fixed effects, while the red series does. Confidence intervals are shown at the 95% level and calculated from standard errors clustered at the pooling-unit level.

3.6 Conclusion

This chapter served two purposes. First, it documented rich and novel empirical patterns in Chinese SI using administrative data. By comparison, a lack of data has and continues to hinder attempts by policy makers and academics to document even basic patterns about SI. Even the IMF, when reporting China's tax-to-GDP ratio, fails to count SI contributions, citing a of lack of data. Second, we document for the first time a major determinant of SI non-compliance: the *de facto* power granted to local governments under SI decentralization. Given the extent of non-compliance documented here, and the evidence suggesting that local tax authorities can expand the tax base if motivated, base expansion would seem to be a primary policy lever in meeting China's growing expenditure needs.

Chapter 4

How Well-Targeted are Payroll Tax Cuts as a Response to COVID-19? Evidence from China

Governments around the world enacted large stabilization measures in 2020 to respond to economic downturns caused by the COVID-19 pandemic. The mitigation of employer obligations for payroll taxes or social insurance (SI) contributions featured prominently in these policies [IMF, 2020; International Labour Organization, 2020]. Many countries permitted deferrals of payments of SI premiums, while a smaller but still significant number of countries—both high-income countries like Finland, Norway, and Sweden and emerging economies like Argentina and Thailand—enacted temporary payroll tax cuts (Table C.1).

China adopted perhaps the most substantial payroll tax cut. It completely exempted most firms from the employer portion of three types of SI contributions—pension, unemployment, and workplace injury—for 11 months in 2020. The exemption reduces the payroll tax rate by 21 percentage points (p.p.) on average. In addition, employer contributions to mandatory medical insurance (MI) were also reduced by half for 5 months in certain regions. China also stands out in its reliance on payroll tax mitigation as the main component of its fiscal response to COVID-19: the cost to the nation's SI system was estimated to exceed CNY 576 billion for the first half of 2020[55], dwarfing the cost of other COVID-19-related tax cuts such as the reduction of small taxpayers' VAT rate.

The mitigation of employer contributions to SI should improve business cash flow and reduce labor costs, which directly support business retention of workers during the downturn, increase the probability of firm survival, and even facilitate the hiring of new workers during COVID-induced reallocation. In these regards, short-term payroll tax cuts share the aims of many other temporary measures adopted to support business liquidity and encourage worker retention, but may be superior in certain regards. For instance, the benefits of payroll tax cuts are delivered immediately through taxpayer self-assessment, making them administratively simple and avoiding mis-allocations that could arise from using financial intermediaries [Bonomo et al., 2015; Granja et al., 2020; Ornelas et al., 2019]. Yet the use of payroll tax cuts as a response to COVID-19 has received little attention in the economic literature.

[55] http://www.xinhuanet.com/fortune/2020-07/27/c_1126287738.htm

In this study we analyze the distribution of China's 2020 reductions across firm sizes and sectors, in part to address one potential critique of such policy: that these cuts may deliver windfall benefits to large, resilient firms, while delivering insufficient support to the firms and sectors most vulnerable to the downturn. Additionally, we consider the degree of SI non-participation (labor informality), which is a significant consideration for policy effectiveness in China and many other developing countries with large informal economies [Loayza and Pennings, 2020].

We use a unique administrative taxpayer data set from one large province in China that covers all tax-registered firms in the province, a critical advantage over other data sets that have been used to study SI in China. Since China is unusual among developing countries in having a very low degree of *firm* informality (non-registration with tax authorities),[56] the data set covers essentially all firms in the province. This allows us to directly observe the prevalence of *labor* informality, in this case manifesting itself as non-participation in SI. Non-participation in SI is widely understood to be commonplace in China even among firms that report deductible wages on their corporate income tax (CIT) returns.[57] We use our data to quantify the size of the economy that is out of reach of payroll tax cuts, whereas it may be difficult to find data to make the same calculations in other countries where firm informality is prevalent.

We find that because SI contributions represent one of the largest business tax bases, payroll tax cuts allow the government to confer meaningful and immediate benefits to firms. While labor informality reduces government support to small firms, the regressive tax structure of SI contributions, and the greater labor intensity of small firms and sectors affected by COVID-19, target benefits to vulnerable and affected firms that participate in the SI system. More specifically:

Coverage and Magnitude of the Tax Cut: SI contributions account for 20% of total taxes remitted by firms, or 13% when considering only the employer portion.[58] Among firms that participate in SI, the average value of the SI tax cut is 2.1% of total annual business costs and the tax cuts reduce the median average tax rate (ATR) on labor by 21.25 p.p. However, 54% of active firms—representing 24% of aggregate economic activity—do not make SI contributions, and therefore receive no support from the policy.

Distribution of the Tax Cut Across Firm Size: Only 22% of the smallest decile of firms make SI contributions compared to 78% of the top decile. However, despite non-participation, we find that because of the greater labor-intensity of small firms, on average they still receive greater

[56] The China Taxation Yearbook (2002) reports outcomes for tax registration of newly established businesses in 2000 for the entire country, and across 31 provincial and 5 prefectural jurisdictions (pp 621-2, 627-8). The national average rate of registration for the State Tax Bureau (guoshui) system was 97% (out of 8.659 million firms and individual proprietors), while it was 95.7% for the Local Tax Bureau (dishui) system (out of 6.135 million firms and individual proprietors). While no similar national statistics has been published since then, internal reports within Chinese tax administration quote similar high rates of registration for more recent years.

[57] The importance of distinguishing between firm and labor informality has been stressed by recent work [Ulyssea, 2018, 2020].

[58] Our data on tax remittance includes only the employer portion of SI contributions and does not include employee contributions withheld by the employer.

subsidies relative to their costs and liquidity than do large firms. Among the lowest decile of firms that participate in SI, the subsidy accounts for 10% of annual expenses. This is approximately 16% of liquidity that the median small firm has available. Additionally, because the SI system creates high ATRs for low-wage firms, the tax cut reduces median ATRs among the smallest firms by approximately 40 p.p.

Correlation with Exposure to the Economic Downturn: To measure whether assistance is proportional to firms' exposure to the economic shock, we rely on estimates of sales declines across industry and firm size categories reported in Chen et al. [2020b]. We find that industry-level benefits from the tax cut are weakly positively correlated with industry exposure to the economic downturn. This is largely driven by the greater labor-intensity among affected industries. By contrast, different SI participation patterns across sectors do not undermine the targeting of tax cuts to vulnerable sectors.

Our work contributes to several strands in the evolving literature on governmental responses to COVID-19. The first comprises studies using pre-2020 administrative data to project the distribution of fiscal relief [Alstadsaeter et al., 2020; Ganong et al., 2020; Bachas et al., 2020; Brockmeyer and Bachas, 2020]. A second strand analyzes various forms of subsidies for job retention [Bartik et al., 2020; Bennedsen et al., 2020; Birinci et al., 2020; Chetty et al., 2020; Granja et al., 2020; Kaplan et al., 2020], such as the U.S. Paycheck Protection Program. Payroll tax cuts both bear analogies and present distinct alternatives to these policies. Third, our study may be the first to empirically analyze the role of labor informality in determining the effectiveness of policies targeted at businesses in response to COVID, adding important insights to the literature on the appropriate government response to the pandemic in developing countries [Alon et al., 2020; Bruhn, 2020; Loayza and Pennings, 2020; Alfaro et al., 2020].[59]

Finally, our distributional findings complement early preliminary evidence suggesting that payroll tax mitigation bolstered Chinese firms' ability to weather the economic downturn. Based on a survey of limited sample size (2,044 firms), Chen et al. [2020a] indicate that deferrals of SI contributions provided by Chinese cities in early February 2020 improved the cash flow of small and medium enterprises (SMEs) in the first months of the pandemic, whereas government-supported lending did not. With respect to the subsequent SI contribution cuts that are the focus of our analysis, the surveyed firms also report that they improve cash flow, re-opening, and the likelihood of having a majority of employees return to work. Likewise, Chen et al. [2020b] claim that China's payroll tax exemptions had a positive effect on business activities (measured in terms of sales) during February

[59] Our work also contributes to a nascent literature on Chinese social insurance [Fang and Feng, 2018]. Early efforts to investigate firm participation relied on small firm samples [Maitra et al., 2007; Nielsen and Smyth, 2008; Nyland et al., 2011]. Subsequent research turned to the National Bureau of Statistics (NBS) survey of large private industrial and state-owned firms [Gao and Rickne, 2014, 2017; Rickne, 2013], but NBS data excludes small firms and all privately-owned firms in the service sector. These firms represent a large share of the aggregate economy and are highly affected by the COVID-19 shock. Our data contains both small firms and service industries, which allows us to study SI participation across all sectors and to characterize the likely distribution of fiscal relief achieved through the payroll tax cut.

to April. These recent studies highlight the need for studying the implied distribution of fiscal support.

4.1 Policy Background

In the mid- to late-1990s, China adopted a mandatory “pay-as-you-go" pension system, Basic Old Age Insurance (BOAI), for employed persons funded mainly through employer statutory contributions (see Fang and Feng [2018] for a history of pension programs in China). Likewise, in the early 2000s, a medical insurance (MI) program for employed persons was established, also funded by payroll taxes. These two programs are the largest components of the SI system. As of 2016, the employer contribution rate for BOAI and MI was 20% and 8% of wages, respectively. BOAI and MI also require employee-side statutory contributions— 8% for pension and 2% for medical— which are recorded in notional individual accounts that are also effectively pay-as-you-go [Fang and Feng, 2018].

Beginning in late January, 2020, many Chinese cities announced economic stabilization policies in response to COVID-19. The two most frequently-mentioned measures were the deferral of the employer portion of SI contributions and partial refunds of prior-year unemployment insurance (UI) contributions for firms that retain their employees. The wide adoption of these measures is explained by the fact that both pre-dated 2020. Since 2011, China's Ministry of Human Resources and Social Security (MOHRSS) had allowed discretionary grants of SI payment deferrals. Because China's SI budgetary units are highly fragmented, the authority for granting such deferrals frequently rested with county-level SI administrations. In early February 2020, cities began to announce eligibility standards specifically applicable to the COVID-19 emergency: some jurisdictions aimed at precise targeting, while others tied deferrals to job retention. The policy of refunding 50% of prior-year employer UI contributions not only predated 2020 but was in fact a national directive: since 2014, China's State Council, MOHRSS and other national ministries have promoted this policy to encourage job retention for firms under financial distress. As with the deferral of SI contributions, eligibility criteria for UI refunds varied considerably across jurisdictions.

The national policies introduced on February 20, 2020 by MOHRSS[60] superseded these prior policies and provided a far larger stimulus. First, they entailed a temporary exemption or reduction for three types of SI contribution (pension, unemployment, and injury). As initially announced in February, all firms other than “large firms” and all individual proprietors received an exemption from employer contributions for 5 months (February-June); and all large firms and private non-business organizations received a 50% reduction in contribution obligations for 3 months (February-April).[61]

[60] Notice by the MOHRSS, the Ministry of Finance and the State Taxation Administration of the Temporary Reduction and Exemption of Social Insurance Premiums Payable by Enterprises, MOHRSS No. 11 (2020).

[61] The Ministry of Industry and Information Technology (MIIT) sets revenue, asset, and employee thresholds for each industry which determine whether firms are Micro, Small, Medium, or Large. The revenue threshold delineating

On June 22, 2020, MOHRSS extended the exemption for the first group of firms to the end of 2020, and the 50% reduction for the second group of firms to June.[62] Second, delays in SI contributions for firms that have residual obligations were allowed for up to 6 months (and must end by December 2020). Firms were now automatically eligible for such delays and no application was necessary.

On February 21, 2020, China's Nation Healthcare Security Administration announced guidelines for mitigating employer contributions for MI[63]. Under these guidelines, local jurisdictions that form medical pooling units may in principle *either* reduce employer MI contributions by half for 5 months (February to June) *or* continue any prior practice of providing for deferrals of contributions for up to 6 months. The choice depended on whether the pooling unit's cumulative balance provided sufficient cushion for current expenditures. In contrast, the MOHRSS-announced tax cuts apply in conjunction with payment deferrals. These guidelines leave greater discretion to local governments than the MOHRSS-announced policy, reflecting the fact that medical pooling in China is even more fragmented than for other types of SI. As the rates for employer medical contributions vary across pooling units (within provinces and even within some prefectures), the magnitude of any tax cut also varied. In the province we study, all prefectures chose to adopt rate reductions instead of payment deferrals for MI contributions, with the rate reduction ranging from 3 p.p to 4.5 p.p. In the analyses below we include the temporary MI rate cuts in calculating benefits to firms, while reminding readers that such cuts may not have been uniformly adopted in China.

The combined tax rate of the pension, unemployment, and injury contributions that statutorily fall on firms was on average 21% and 17.25% in 2016 and 2019, respectively, in the province represented in our data. Medical and maternity insurance constituted 8.6-8.7%. Across all categories, the combined rates were 29.6% and 25.93% in 2016 and 2019 respectively, some of the largest in the world. The temporary measures in place from February to June lowered rates by 21.25 p.p. for non-large firms and 10.625 p.p. for large firms. The July to December provisions lowered rates by 17.25 p.p. for non-large firms but reinstated the full rates on large firms.

SI obligations are determined on a monthly basis in China. The rate (τ) for each category is applied to each employee i's monthly wage w_i to determine the liability for that employee. However, w_i is bounded above and below by $[.6\bar{w}_c, 3\bar{w}_c]$, where $\bar{w}_c$ approximates the average monthly wage in city c, to create a minimum and maximum SI contribution per employee. Panel A of Figure 4.1 illustrates this schedule. Panel B shows the derivation of marginal and average tax rates (ATR) for a given monthly wage, and compares the statutory rates in 2016 to those in 2019.

Among firms with participating workers, the collared structure has implications for the nature

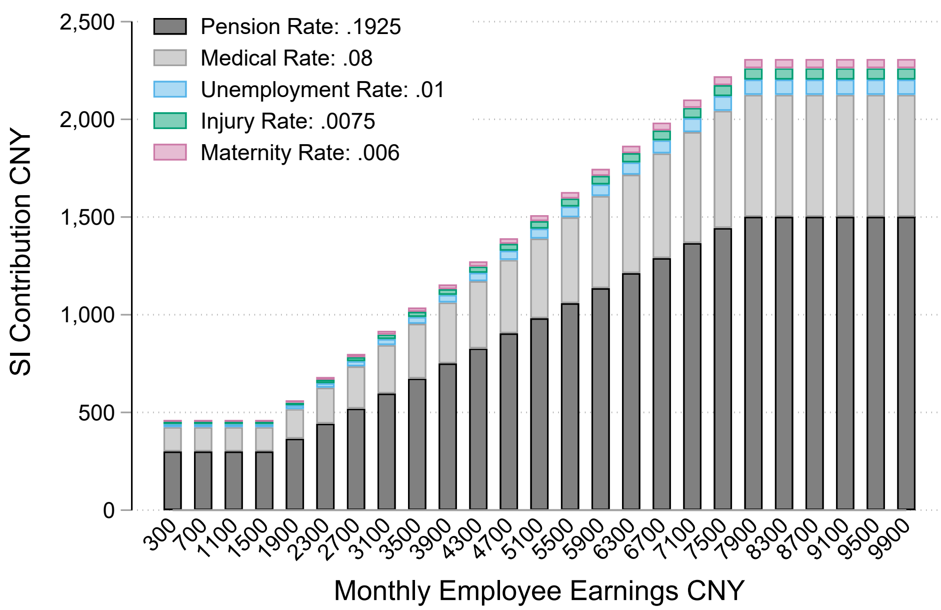
medium from large ranges from CNY 20,000,000 for Agricultural firms to CNY 2,000,000,000 for Real Estate firms. Table C.7 shows the full set of revenue thresholds.

[62] Notice by the MOHRSS, the Ministry of Finance and the State Taxation Administration of Extending the Implementation Period of the Policies Regarding the Temporary Reduction and Exemption of Enterprises' Social Insurance Contributions and Other Issues, MOHRSS No. 49 (2020).

[63] Guiding Opinions of the National Healthcare Security Administration, the Ministry of Finance and the State Taxation Administration on the Temporary Reduction of the Premiums of Basic Medical Insurance for Employees, National Healthcare Security Administration No. 6 (2020).

Figure 4.1: **The SI Employer Contribution Schedule**

a **2016 Rates**



b **Marginal and Average Tax Rates**

	$w_i < .6\bar{w}_c$	$w_i \in [.6\bar{w}_c, 3\bar{w}_c]$	$w_i > 3\bar{w}_c$
MTR	0	τ	0
ATR	$\tau \times \frac{.6\bar{w}_c}{w}$	τ	$\tau \times \frac{3\bar{w}_c}{w}$
Category		$100 \times \tau_{2016}$	$100 \times \tau_{2019}$
Pension		19.25	16
Unemployment		1	.5
Injury (Inferred)		.75	.75
Medical		8	7.88
Maternity		.6	.8
Total		29.6	25.93

Note: Panel A illustrates the schedule for SI remittances for a fully compliant firm using 2016 rules. The tax base w_i is the monthly wage for employee i. The SI contribution statutorily required by the employer is the base multiplied by the statutory rate τ. The taxable base is bounded below and above by $.6\bar{w}_c$ and $3\bar{w}_c$, where $\bar{w}_c$ approximates the average monthly wage in city c. Panel B illustrates implicit marginal and average payroll tax rates. The marginal payroll tax rate for an employee is the increase in SI contributions when the firm increases the employee's monthly wage by a dollar. The average payroll tax rate is the ratio of total SI contributions for an employee over that employee's monthly wage. Panel B also compares the statutory rates in 2016 to those in 2019.

of labor adjustment and the effect of cutting SI taxes. First, for firms paying monthly wages outside of $[.6\bar{w}_c, 3\bar{w}_c]$, the marginal tax rate on each employee's additional earnings is zero. In contrast, the ATR is non-zero and substantial for all firms. As a result, SI tax cuts may have a limited effect on intensive margin adjustment (monthly hours or wages per worker) and more substantial effects on extensive margin decisions (job retention and hiring). Second, low-wage firms ($w_i < .6\bar{w}_c$) face the highest ATRs, and as a result, receive the largest ATR reduction from the temporary exemption. Third, because the minimum contribution is applied monthly, rather than annually, firms may have even stronger incentives to lay off employees in the face of temporary demand shocks.

Finally, non-participation is a major feature of the SI system as actually practiced. Official statistics suggest that in spite of the compulsory nature of these programs, only 68.7% of urban employees participated in 2017 [Fang and Feng, 2018].[64] While this large compliance gap is no doubt attributable in part to high nominal contribution rates, scholars have also conjectured that non-enforcement may be just as important a factor. Some argue that local officials are likely to limit enforcement, as this mitigates the adverse effect of SI collection on business formation and growth. Another common conjecture is that the administrators designated to collect SI contributions may lack the resources needed for full enforcement.

4.2 Data and Sample

4.2.1 Tax Return and Financial Statements:

We use an administrative data set from a large province in China containing financial records, tax returns, tax remittance, and tax registry information for the universe of firms in 2016.[65] This data provides two advantages for describing the nature of firm participation in SI. First, it contains all tax-registered firms, including those that do not make SI contributions. China is unusual in having a very high degree of tax registration such that most labor informality manifests at tax-registered firms, as opposed to labor hired by non-registered, informal firms.[66] As a result, we can offer a unique view of the varying degrees of labor formality across the entire firm-size distribution.

Second, the universal coverage and recency of the data provides significant advantages over

[64] A government think-tank estimates that in 2015, 70% of all firms that participated in SI under-contributed relative to statutory requirements [Feng and Faqiang, 2019]. See also Tang and Feng [2019] for additional citations. Li et al. [2021] report a median effective contribution rate (SI payments over total firm wages) of only 0.9% in the NBS sample of firms they study.

[65] This data set was first used in Cui et al. [2020] to study tax preferences for investment in the corporate income tax. The current paper presents the first analysis of social insurance patterns.

[66] The combination of high firm formality and high labor informality in China is discussed in Chapter 3 of Cui [2021]. The China Taxation Yearbook (2002) reports outcomes for tax registration of newly established businesses in 2000 for the entire country, and across 31 provincial and 5 prefectural jurisdictions (pp. 621-2, 627-8). The national average rate of registration for the State Tax Bureau (*guoshui*) system was 97% (out of 8.659 million firms and individual proprietors), while it was 95.7% for the Local Tax Bureau (*dishui*) system (out of 6.135 million firms and individual proprietors). While no similar national statistics have been published since then, internal reports within Chinese tax administration quote similarly high rates of registration for more recent years.

existing literature. Existing research has relied on either a survey of approximately 2,200-5,400 audited firms from Shanghai in 2001 and 2002 [Nyland et al., 2006; Maitra et al., 2007; Nielsen and Smyth, 2008] or the NBS Survey of Industrial Firms for years 2001 to 2007 [Gao and Rickne, 2017; Rickne, 2013]. The latter contains all State-Owned Enterprises (SOEs) and private industrial firms above 5 million CNY ($800,000) in revenue. These criteria would exclude 88% of the firms (representing 65% of employees) in our data. Furthermore, the Chinese SI landscape has evolved considerably since 2001-2007.

Table C.2 reports the number of tax-registered firms from our cross-section (we exclude non-business entities and individual proprietors). We observe 1.4 million firms in the tax registry; 1.05 million of which filed non-empty financial returns; 902,000 of those reported positive revenue and costs on their financial return; and 879,225 of this last set had non-zero tax remittance (in any tax category). We take the 893,402 firms as our analysis sample under the intuition that firms without any tax remittance or revenue/costs are likely inactive entities.

We use several variables from this data set:

Tax Remittances: We observe all tax remittances made throughout the tax year, net of any refunds. We collapse tax remittances into 5 general categories: SI contributions, value-added tax (VAT) and sales taxes, CIT, personal income tax (PIT, which are withheld by firms), and other taxes.[67] Total taxes paid by a firm are the sum across these categories.

Firm Inputs and Outputs: Total wages paid for the tax year are reported on the CIT return inclusive of SI contributions (which are CIT deductible). We calculate net-of-SI wage expenses by substracting total SI remittances from the CIT wage bill. The number of employees is reported in the tax registry which we observe a snapshot of for 2017. This record reflects information gathered at the most recent time in which the firm's registration information was updated. Firms are prompted to update the information annually, although we do not observe the date of the most recent update, so the employee number may sometimes reflect employment from earlier years. Additionally, this point-in-time measure does not reflect turnover in the workforce throughout a given year. The measure of employees, therefore, is observed with error. Finally, we use revenue as reported on financial statements as our primary measure of firm size.

Total Costs and Liquidity: We define total costs as the sum of (i) costs of goods sold and (ii) business expenses. The former is an approximation of the "direct cost" of the goods and services produced. Business expenses are overhead costs, including sales and management expenses (but excluding financing expenses). Labor costs are included in both and apportioned according to these definitions. We define a firm's liquidity as the total value of liquid assets reported on its balance sheet, which includes cash holdings.

Industry Classifiers: Finally, the tax registry provides detailed industry codes, which allow us to

[67] Sales taxes include the Business Tax (*yingyeshui*) and Excise Tax (*xiaofeishui*); the former was replaced by the VAT in 2016. Other taxes include deed and property taxes; land value, maintenance, and use taxes; resource tax; vehicle taxes; and stamp duty.

merge in external measures of the Covid-induced shock for each industry.

Table 4.1 reports summary statistics for each of these variables. The median firm earns 1,360,000 CNY ($226,666) in annual revenue and holds approximately the same amount in liquid assets. On average, firms employ 15 workers at an average annual wage of 91,000 CNY. This compares to the locally-set statutory mean wage (w_c) of 68,000 CNY.[68] Finally, the first column of Table C.6 shows the fraction of firms in each aggregate industry category. Over one third of firms are in manufacturing industries; one fifth in wholesale; 12% in retail; 8% in business services; and 6.5% in construction.

Table 4.1: **Descriptive Statistics**

	Mean	P25	P50	P75	P90	P95	N
Revenue(10000s)	1302	35	141	547	2142	5346	870868
Costs(10000s)	1238	39	145	545	2086	5114	870868
Total Assets(10000s)	1790	53	166	595	2400	6811	870868
Liquid Assets(10000s)	1201	46	136	483	1705	4557	869066
Employees	16	3	6	10	30	60	870862
Net of SI Total Wages(10000s)	80	0	9	38	155	376	870868
Mean Wage	91611	14814	35233	80500	191950	354243	611522
Statutory Mean Wage	68612	67200	67200	72980	72980	72980	870868

Note: This table shows the means and percentile values, at the firm level, for key variables used throughout the paper. Statutory Mean Wage is the statutorily defined local mean wage w_c (in CNY) used for the purposes of determining minimum and maximum SI contributions per employee, multiplied by 12, since w_c is defined as monthly earnings. This mean is weighted by the number of firms in the local area for which the local mean wage is defined. Variables are winsorized at the 1st and 99th percentiles before calculating averages.

4.2.2 Representativeness

To assess the representativeness of this province, Tables C.3 and C.4 compare the industry and ownership composition of our data to that of nationally-reported statistics from the China Statistical Yearbook (CSY). Since the CSY covers industrial firms (i.e. manufacturing, mining, or energy and utilities) that are either (a) state-owned, or (b) report revenues greater than 20 million CNY, we report statistics for the 48,995 firms in our 2016 data that fit these criteria. The province that we study is somewhat more manufacturing-intensive, and substantially less mining-intensive, than China as a whole. The size of the utility sector is approximately comparable to its size nationwide. The province has a smaller share of enterprises in agriculture- and forestry-related manufacturing, mineral products, and electrical power generation.

We also assess whether 2016 data is likely to reflect the distribution of SI payments in 2019. To do

[68]This works out to 15 $\times$ 91,000 = 1.36 million in total wages, which is more than the reported average total wages of 790,000. The discrepancy derives from our calculating the mean wage per employee among the set of firms with positive total wages, as reflected in the smaller N.

so, we collected official budgetary figures for each of the province's local SI pooling units in 2016 and 2019. Figure C.1 plots BOAI revenues and outlays for 2019 against those for 2016. After accounting for inflation, pooling unit revenues and outlays rise by 27% and 40% between 2016 and 2019, respectively. While these growth rates are large, 2016 figures are extremely predictive of 2019 figures. Since the pooling units vary meaningfully in terms of firm size and industry mix, we would not expect such high correlations between 2016 and 2019 if the distribution of participation by firm size and industry had changed meaningfully between 2016 and 2019. We take this exercise as suggestive evidence that 2016 participation rates are a meaningful proxy for participation immediately before the COVID-19 pandemic.

4.2.3 Sales Shocks from VAT Transactions:

Finally, Chen et al. [2020b] use 1.5 billion VAT transactions in China, from January 1, 2019 to April 16, 2020, to estimate how firm sales changed in the twelve-week period following the onset of Wuhan's lockdown (January 23, 2020). Specifically, they estimate the average percent change in total sales filed through the VAT reporting system, relative to the same time in 2019, for 4 firm size bins and 18 industries resulting in 72 bins, which we use to merge into our data. [69] We use this information to examine the correlation between exposure to economic shocks and the magnitude of the SI tax cut. We use the estimated sales change for the 4-week period of March 26 to April 16, 2020, as this provides a better measure of the medium-term effect than the initial substantial drop in January and February. One caveat is that transactions made by small firms that are exempt from the VAT are excluded, and so revenue changes are better measured for larger firms.

4.3 Results

4.3.1 Magnitude of SI Remittance and Participation

We begin by documenting the magnitude of firm SI remittances as a fraction of their total tax payments. We contrast SI remittance against four other categories of tax remittance—CIT, VAT and sales taxes, PIT withholding, and all other taxes (such as property taxes)—to illustrate the size of SI contributions relative to other tax levers the government has at its disposal.

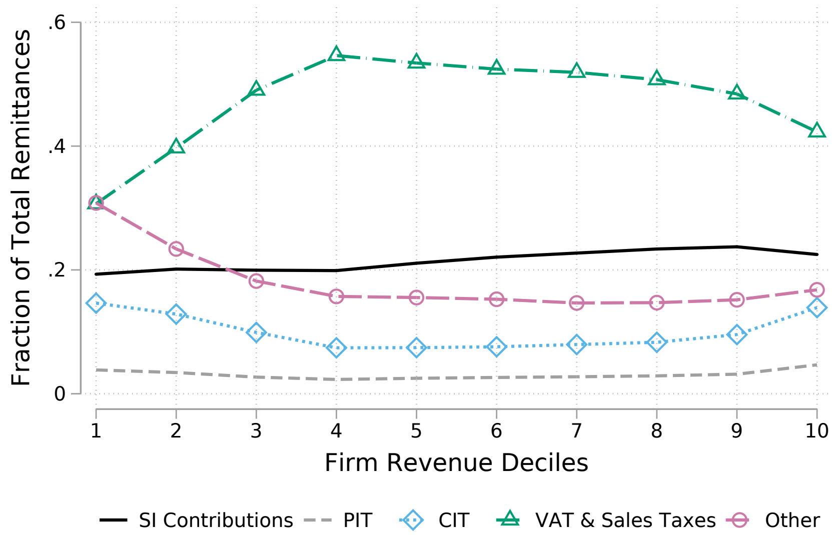
In particular, we split firms into revenue deciles d.[70] Then for each decile d and tax type k, we calculate $\frac{1}{N_d}\sum_{i\in d}\frac{t_{i,k}}{\sum_k t_{i,k}}$ where $t_{i,k}$ is the amount remitted by firm i for tax k. Figure 4.2 plots the results. SI contributions make up approximately 20% of firms' total tax remittances and this fraction increases with firm size, ranging from 18.7% for the lowest decile to 22.5% in the largest

[69] Their VAT data accounts for 11% of total firm sales in China. The transactions cover 3.9 million unique corporations and 1.7 million self-employed. The authors construct size bins using annual firm revenue from 2019 following the MIIT size revenue cutoffs.

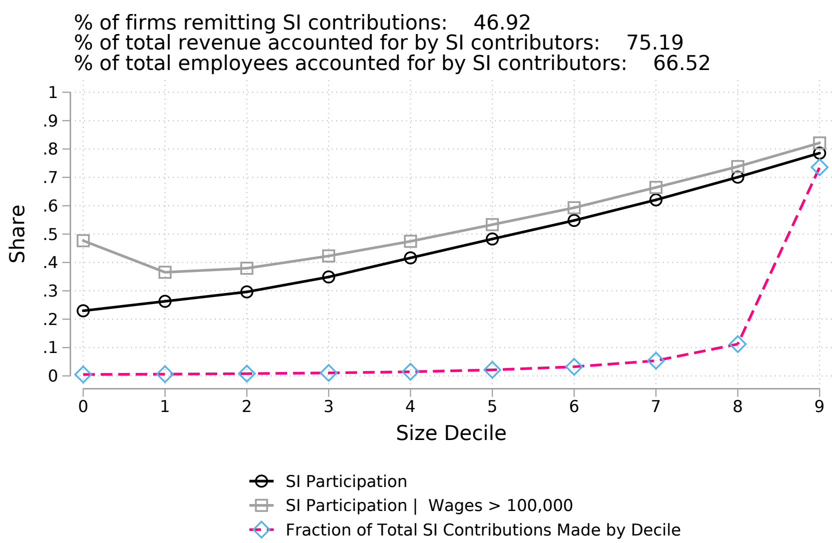
[70] Table C.5 provides the decile cutoffs.

Figure 4.2: **Firm Remittances Across Tax Types**

a **Tax Composition**



b **SI Participation**



Note: For each firm revenue decile, Panel A shows the fraction of total tax remittances accounted for by each of the five main tax categories: SI contributions, personal income tax withholding, corporate income tax, VAT and other sales taxes, and all other tax payments. That is, for each decile d and tax type k, we calculate $\frac{1}{N_d}\sum_{i \in d} \frac{t_{i,k}}{\sum_k t_{i,k}}$. $d = 1$ is the smallest decile and $d = 10$ is the largest. In Panel B, the black series plots the fraction of firms that remitted SI contributions in 2016 in each firm size decile. Approximately 46% of active firms remitted SI contributions. Only 22% of the smallest decile participate, while 78% of the largest decile do. The grey series plots the fraction of firms within each decile that remitted SI contributions out of a restricted sample of firms that (1) reported a positive number of employees and (2) more than CNY 100,000 in wages on their corporate income tax returns. The dashed magenta series plots the fraction of aggregate SI remittance that was made by each firm decile. The top decile of firms contribute 73.8% of all SI contributions.

decile. For the top eight revenue deciles, SI contributions are the second highest share of taxes paid next only to VAT and sales taxes. This suggests that payroll tax cuts have the potential to deliver some of the most significant cash benefits to businesses compared to other tax policy levers.

Panel B characterizes firm participation in SI, defined as making any SI contributions. First, note that only 46% of firms — who account for 76% of aggregate revenue — make SI contributions. This leaves 54% of firms and 24% of economic activity out of the reach of the SI cut. Second, and unsurprisingly, non-participation is much higher among small firms: only 22% among the smallest firms, and gradually rising to 78% among the largest. The largest decile of firms account for 73.8% of total SI contributions. Panel B also shows that this pattern of non-participation obtains in a restricted sample of firms that reported (1) a positive number of employees and (2) more than CNY 100,000 in wages on CIT returns.[71] This pattern of labor informality ensures that a greater portion of large firms receive the benefits than of smaller firms.

4.3.2 Average Tax Rates Generated by the SI Contribution Schedule

We next turn to the ATRs generated by SI obligations. A reduction in the ATR among participating firms directly affects their extensive margin employment incentives—how many workers to hire and retain. This is crucial given that a central objective of the temporary rate cut is to induce firms to maintain employment.

We construct ATRs as follows. For each firm, we divide its total wage bill by the number of employees, then further divide by twelve to calculate the monthly wage per employee. With the monthly wage, we calculate an ATR following the ATR formula in Panel B of Figure 4.1. To visualize variation across firm sizes, Panel A of Figure 4.3 plots the median ATR, using 2016 rates, for each size decile separately for SI contributing firms and non-contributing firms.

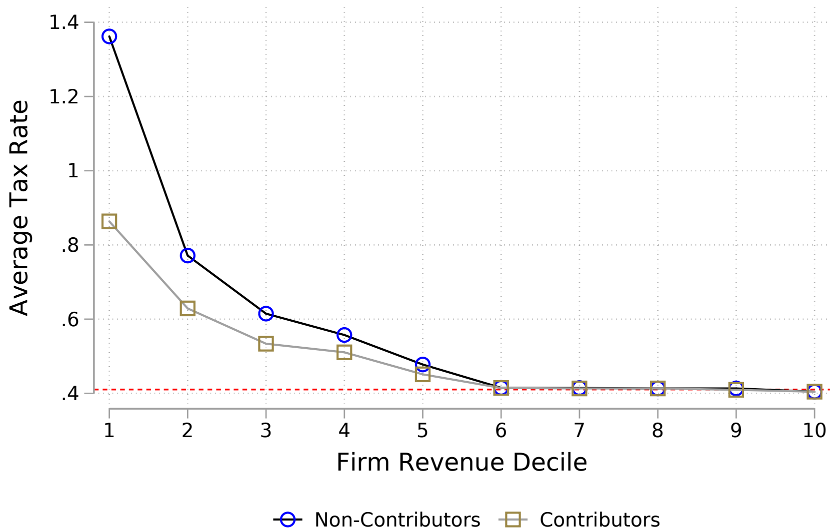
Two facts are apparent. First, the ATR is greater than the statutory rate (τ) for the lower half of the firm distribution. This is caused by low monthly wages at smaller firms, often below the minimum SI wage base. In the upper deciles, the ATR is equal to the statutory rate, reflecting the fact that the upper bound on the taxable wage does not bind on average. Second, among the bottom half, SI contributing firms have lower ATRs. This suggests that firms select into SI based on the ATR they face, and that part of the labor informality gradient is driven by higher ATRs among smaller firms.

Panel B explores the effect of the COVID tax cut. We keep only SI contributing firms—since only they stand to benefit from the cut—then calculate the median ATR as described above. We show the implied ATRs for (i) 2019, (ii) February to June 2020, and (iii) July to December 2020. In 2019, median ATRs are 25.93% for the top five firm deciles, and up to 52% for the lowest decile. The February-to-June-2020 exemption of pension, UI, and injury contributions, and the 50% reduction

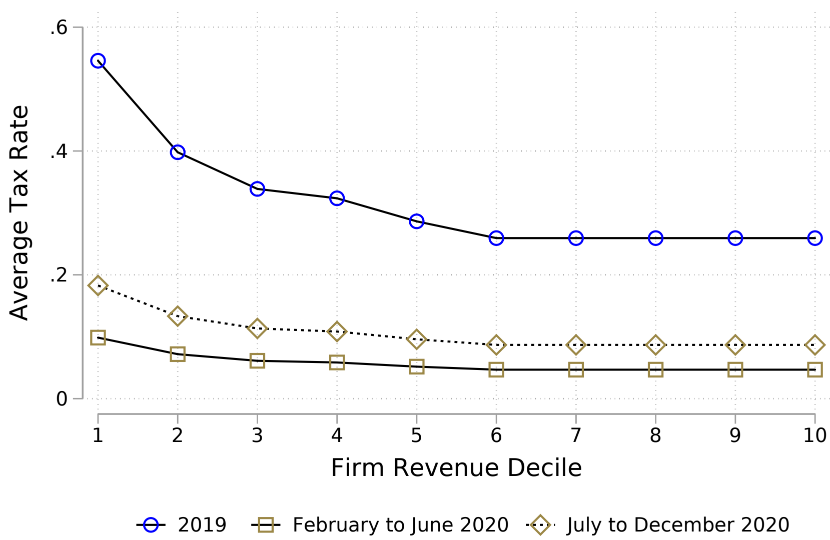
[71]CNY 100,000 is approximately 8 months of work for a single employee earning the statutorily-set mean wage (w_c).

Figure 4.3: **Average Tax Rates**

a **Average Tax Rates in 2016**



b **Effect of 2020 Cuts Among SI Contributors**



Note: Panel A plots the average tax rate (ATR) for each revenue decile as follows: (1) Revenue deciles are calculated for the full sample. (2) Each decile is split into SI contributing and non-contributing firms, creating 10 × 2 bins. (3) For each bin, the median of firm average monthly wages is calculated. For firm i, its average wage w_i is calculated as its total annual wage bill divided by the total number of employees, then further divided by 12. (4) The ATR is then calculated for each firm following the formula shown in Figure 4.1. (5) The median ATR is then plotted for each bin. The red horizontal line demarcates the combined statutory rate across all contribution categories in 2016. If $w_i \in [.6\bar{w}_c, 3\bar{w}_c]$, the ATR is equal the statutory rate. Panel B repeats this exercise, for contributing firms only, but applying (a) the 2019 rates, (b) the reduced rates available for February to June 2020, and (c) the reduced rates available for July to December 2020. Both panels restrict to firms with positive wages (from corporate income tax returns) and employees (from the tax registry).

in MI contributions, lower median ATRs to 4.68% for the largest 50% of firms and to less than 10% for the smallest. As the 50% reduction in MI contributions expired in June, the median ATRs rise to 8.7% for the largest half of firms, and 17.7% for the smallest. The provisions applying to firms classified as large are not visible since these firms make up only approximately 0.3% of all firms.

Dividing total wages by the number of employees may provide a downward bias of wages when employees are mis-measured, and therefore an upward bias in the ATR. As a robustness check on this division bias, in Figure C.2 we instead calculate ATRs in each decile based on the decile's aggregate wage. We define the aggregate wage for group g as $\sum_{i \in g} W_i$ divided by $\sum_{i \in g} E_i$, where W_i and E_i denote firm i's annual wage bill and total employees, respectively. By summing within the denominator and numerator, mean-zero measurement error collapses to zero. The trade-off is that the ATR is overly influenced by the largest firms in each decile (high W and E), and so represents a size-weighted estimate. As shown in Figure C.2, however, the resulting patterns in ATRs are qualitatively unchanged.

4.3.3 Estimating the Effective Subsidy Relative to Costs and Liquidity

In addition to maintaining employment, another primary motivation for SI cuts is to provide liquidity by reducing firms' expenses. We turn to this next by estimating the amount of tax savings (which we refer to as subsidy) provided by the SI cut, and how well-targeted that subsidy is. Our approach is to pose the counterfactual question: *If a firm's total wage bill remained constant, how much would the SI cuts generate in tax savings*? As an alternative, we will also consider the case where employment declines in proportion to firm revenue losses. We construct this counterfactual using tax remittance data from 2016 as follows:

1. **Non-Large Firms**: Calculated as 11/12ths of the firm's pension, UI, and injury contributions—corresponding to the complete exemption for 11 months—and 5/24ths of its MI contributions—corresponding to a 50% reduction for 5 months.

2. **Large Firms**: Calculated as 5/24ths of the firm's pension, UI, injury, and MI contributions—corresponding to a 50% reduction for five months.

3. Because statutory rates have declined slightly since 2016 (see Figure 4.1), we shrink 2016 contributions for each contribution type k by multiplying firm i's remittance T_{ik} by $\frac{\tau_{2019,k}}{\tau_{2016,k}}$.

Critical for our inferences is the assumption that the distribution of SI participation did not change markedly from 2016 to the beginning of 2020. Section 4.2.2 showed that while aggregate revenues grew (in real terms). This growth in revenues may reflect some degree of increasing firm participation, and to that extent, our estimates of the subsidy are lower bounds.

Figure 4.4 plots the average of the implied subsidy across the firm size distribution relative to total costs (Panel A) and total firm liquidity (Panel B). The average subsidy-to-costs ratio is .010

(1.0% of costs) across the full sample and .021 among SI contributing firms. Notably, the benefit of the implied subsidy is far more substantial for small firms. Contributing firms in the smallest decile receive an effective reduction in costs of just under 10%, while for firms in the largest decile, the subsidy is less than 1% of costs. This size gradient stems from two sources. The first is the much higher labor intensity of small firms. The second is the regressive tax structure of China's SI contribution scheme. Figure C.4 presents a reduced form decomposition that indicates that differential labor intensity is the primary contributor.

We find similar subsidy size gradients when expressing the effective subsidy relative to firms' total liquidity. The average subsidy-to-liquidity ratio is .016 across the full sample and .034 among SI contributors. The average subsidy in the smallest decile represents 23% of liquidity among contributors compared to approximately 1% in the top decile.

Figure 4.4 indicates that labor informality among small firms dramatically reduces the average subsidy delivered to them. The average ratio of subsidy to liquidity drops from 23% to 3.5% when non-participating firms are taken into account. Nonetheless, the size gradient of subsidies remains weakly negative in the entire population. In this sense, payroll tax cuts have some desirable targeting properties.

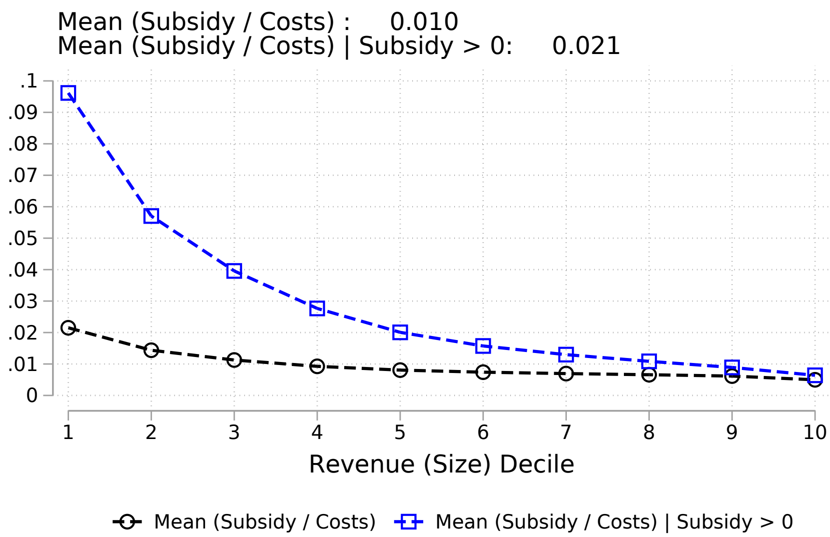
How much liquidity do firms have to begin with? Panel B of Figure C.3 plots the median of cash and total liquidity relative to total annual costs. The median firm has enough cash holdings to cover 12% of normal annual operating expenses. Including all forms of liquid assets, that rises to 83%. Smaller firms tend to hold more liquid assets, relative to operating costs, consistent with them having reduced access to external financing.

Figure 4.4 calculated the value of payroll tax cuts assuming no decline in employment. An alternative assumption is that employment declines in proportion to revenue declines. We factor this into the subsidy calculation by using the estimated revenue declines by industry and firm size bin published by Chen et al. [2020b] (as described in Section 4.2). Panel B of Figure 4.5 compares the baseline subsidy calculation to that where employment — and therefore SI liabilities — decline proportionally with revenue. Under the latter, the average subsidy decreases by 2 percent of total costs, with a large absolute decline among smaller firms who typically had larger revenue declines.

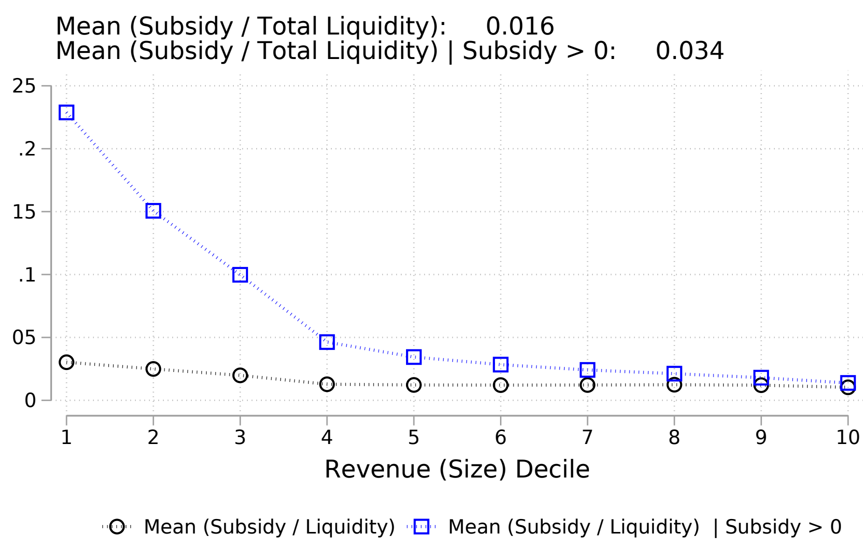
Finally, an alternative definition of targeting is how much of the predicted revenue decline is replaced by the tax savings. Panel B of Figure 4.5 plots the ratio of the imputed subsidy divided by the predicted revenue loss (from Chen et al. [2020b]). Across the whole sample, the SI tax cuts replaced between 5.8% and 6.9% of the revenue loss, depending on whether employment declines are factored in. This replacement ratio is declining with firm size, ranging from over 20% for the smallest firms to 4% for the top decile.

Figure 4.4: **Simulated SI Cut Relative to Operating Costs and Liquidity**

a **Subsidy over Operating Costs**



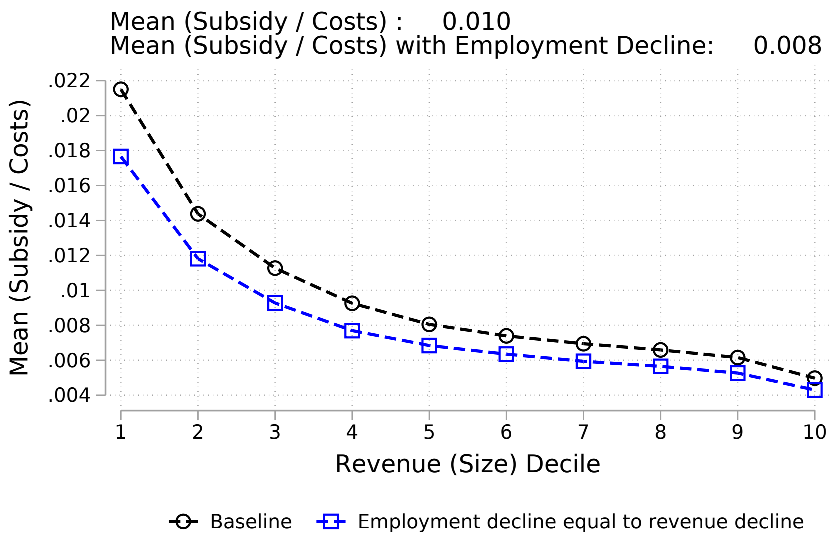
b **Subsidy over Total Liquidity**



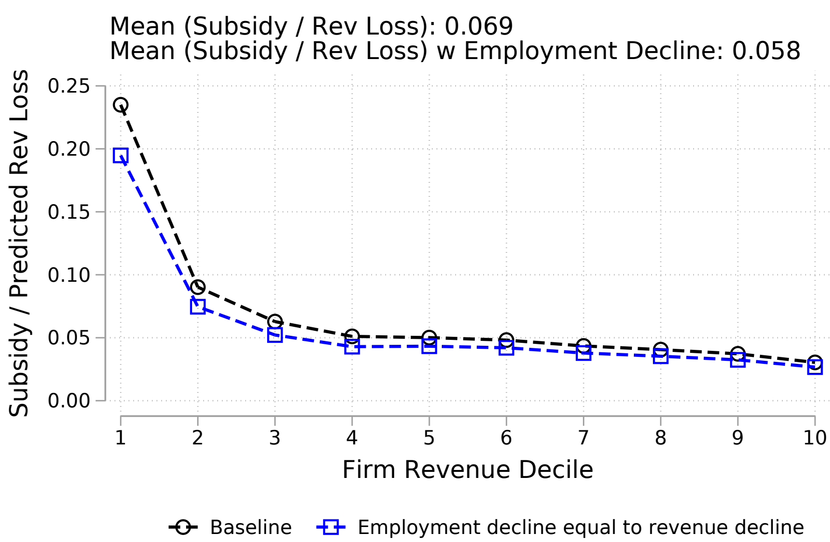
Note: For each revenue decile, this figure plots the mean of the imputed subsidy-over-costs and subsidy-over-liquidity ratios, for both the full sample of firms, and the restricted sample of firms that made contributions to SI (and therefore stand to receive a tax cut). The calculation of the simulated subsidy is described in Section 4.3.3 of the main text. This calculation predicts the size of the tax cut each firm receives if its 2019 payroll is equal to its 2016 payroll. Costs are as reported on firms' financial statements. Liquidity refers to total liquid assets reported on firms' financial statements. The subsidy-to-cost and subsidy-to-liquidity ratios are winsorized at the 5th and 95th percentiles within each revenue decile.

Figure 4.5: **Alternative Simulations**

a **Robustness to Employment Declines**



b **Replacement of Predicted Revenue Loss**



Note: For each revenue decile, this figure plots the mean of the imputed subsidy-over-costs and subsidy-over-liquidity ratios for the full sample of firms. The first series assumes no employment decline, while the second assumes the employment decline in proportion to revenue declines. The calculation of the simulated subsidy is described in Section 4.3.3 of the main text. This calculation predicts the size of the tax cut each firm receives if its 2019 payroll is equal to its 2016 payroll. Costs are as reported on firms' financial statements. Liquidity refers to total liquid assets reported on firms' financial statements. The subsidy-to-cost and subsidy-to-liquidity ratios are winsorized at the 1st and 99th percentiles within each revenue decile.

4.3.4 Targeting Across Sectors

Firm size is just one dimension for assessing whether the stimulus is well-targeted. Exposure to economic shocks varies substantially across industries, with public-facing industries more exposed. To examine how well the SI tax cut directs relief based on economic exposure, we correlate the level of subsidy with the estimated percent change in sales at the industry-size level using the sales estimates in Chen et al. [2020b] (See Section 4.2). There are 4 size groups and 18 industries resulting in 72 bins.[72] For each bin, we sum the implied subsidy and the costs among the firms in the bin, then plot the ratio on the y-axis. Panel A shows that the subsidy is weakly higher among industries with greater sales declines for micro, small, and medium-sized firms. This fact indicates some degree of targeting.

Panel B aggregates up to the industry level. The most affected industries—lodging and food services, education, health and social work, rental and business services, and entertainment—receive a greater subsidy as a proportion of baseline operating costs than unaffected industries. Table C.6 provides a full break-down of measures of the implied subsidy for each industry group. This targeting pattern appears to be driven by differences in labor-intensity across industries, as opposed to differences in participation in SI. Figure C.5 demonstrates that SI participation does not seem to vary with the degree to which industries are exposed to COVID-19 (Panel A) but labor intensity does (Panel B).

4.4 Discussion and Conclusion

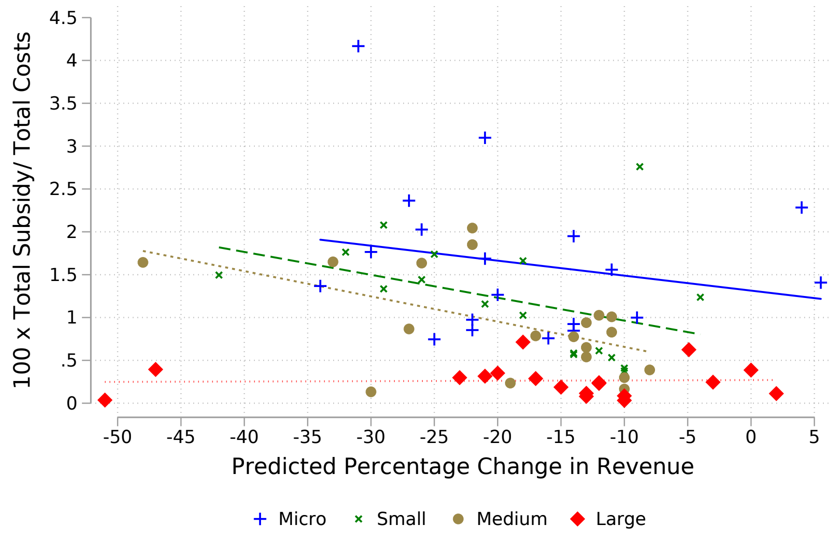
Our analysis of the SI tax base among Chinese firms holds two overall implications. First, among participating firms, SI contribution obligations represent one of the largest tax bases—dominating the CIT base, for example—which allows the government to confer meaningful and immediate benefits to firms during an economic downturn with minimal administrative burden. Second, labor informality severely reduces the reach of these benefits, especially among small firms; yet among the minority of firms that do participate in SI, SI tax cuts are in fact more apt to deliver benefits to small firms. This is for two reasons. One is the regressive tax structure of SI contributions (which is not unique to China): just as low-wage, small firms suffer from a higher ATR under the regular SI scheme, they experience a greater rate reduction during payroll tax cuts (although these firms may still face higher ATRs after a rate reduction than do large firms). The other reason is the fact that small firms are more labor-intensive, and therefore receive larger tax reductions on inputs relative to large firms that rely more heavily on material and capital inputs.

It is useful to consider these conclusions in the context of China's labor markets and the purposes served by payroll tax reductions generally. First, because the minimum contribution rules require

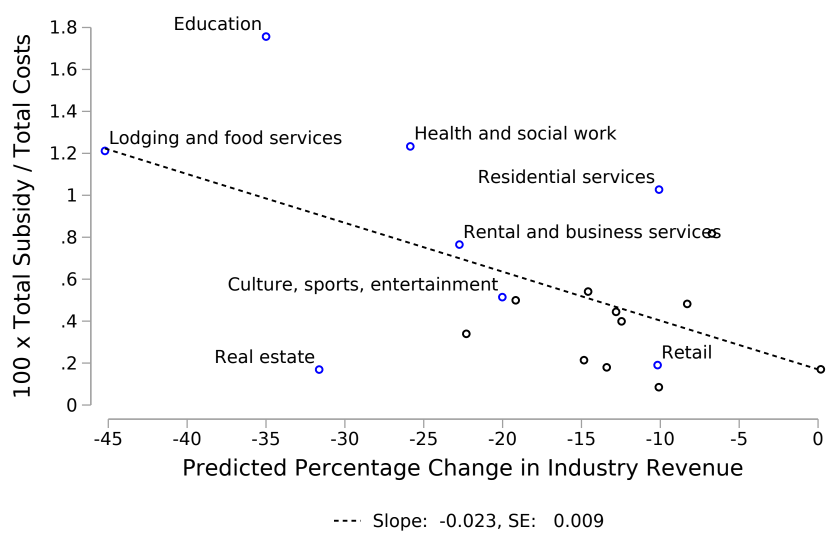
[72]Chen et al. [2020b] construct size bins using annual firm revenue from 2019 following the MIIT size revenue cutoffs.

Figure 4.6: **Subsidy versus Predicted Change in Revenue**

a **Firm Size × Industry Bins**



b **Change in Revenue**



Note: This x-axis is the mean percent change in revenue caused by the COVID-19 shock estimated by Chen et al. [2020b] for the period March 26th to April 16th, 2020 (9-12 weeks following the onset of the Wuhan lock down). They report revenue changes for 4 firm size bins and 18 industries, resulting in 72 bins, which we show in Panel A. The y-axis is the ratio of (i) the bin's total simulated subsidy over (ii) its total operating costs, as reported in our data. The calculation of the simulated subsidy is described in Section 4.3.3 of the main text. Panel B aggregates up to industry bins. To do this, the predicted percent change for an industry is calculated as cost-weighted average among firms of all sizes in that industry. In Panel B, the blue circles denote industries with a text label attached in the graph.

Chinese firms to make SI payments even if employees are temporarily not working (and not receiving wage payments),[73] firms with formal labor arrangements face an additional monthly obligation during a lock-down. Temporary payroll tax cuts provide cash flow to these firms. Moreover, the COVID shock is also a reallocation shock: many firms across numerous sectors are responding to increased demand for new products and services. Barrero et al. [2020] estimate that in the U.S., for every ten jobs lost, three new ones were created. They further argue that labor-retention incentives blunt the productivity gains from this re-allocation. SI rate cuts may improve labor reallocation where cash schemes tied to retention of existing employees do not.

Second, imperfect coverage of small firms is not unique to SI. For instance, in both developed and developing countries (including in the United States [Granja et al., 2020]), government-sponsored credit programs typically struggle to reach small firms [Bonomo et al., 2015; Ornelas et al., 2019]. This is consistent with preliminary evidence indicating that China's COVID lending program did not affect SME firm liquidity or survival [Chen et al., 2020a]. In contrast to such lending programs, payroll tax cuts have the benefit of administrative simplicity and non-reliance on private intermediaries.

Third, we have made positive statements about the extent to which China's payroll tax cuts target small firms and vulnerable sectors. However, an evaluation of such targeting ultimately depends on the normative framework. For example, while payroll tax reductions encourage preservation of the employer-employee relationship, not every employer-employee match has equal social value, and the greatest return to the government's expenditure may come from the preservation of high-productivity matches [Birinci et al., 2020], which may be in the formal sector. Further, turnover in formal matches may be more costly, increasing the social value of retention of formal matches relative to informal ones. On the other hand, the destruction of low-productivity matches may have long-lasting economic effects if these workers find it especially difficult to re-establish employment [Gregory et al., 2020]. These perspectives suggest that normative evaluations of the exclusion of firms that rely on informal labor from government assistance may be complex.

In conclusion, using Chinese taxpayer data, our study offers what may be the first calculation of the extent of COVID-19-related government assistance to employers through payroll tax cuts in a high-informality setting. Our use of Chinese administrative data offers a perspective not only on policy developments in one of the world's most important economies, but also—and equally importantly—on a critical question that faces all of the world's developing economies: how much does government intervention matter when the informal economy is very large? The high level of firm tax registration in China means that the large population of firms that we observe as not participating in SI would have simply been unobserved informal firms in other countries. Because Chinese administrative data allows us to observe such would-have-been-informal firms, we

[73] The practice of furloughs is new to China and there are no direct legal provisions for it, though it has become more widely discussed because of COVID-19—employment lawyers claim to have facilitated such arrangements on a purely contractual basis.

can uniquely quantify the degree to which informality alters the effectiveness of payroll tax cuts.

Chapter 5

Transitioning to Value-Added Taxes: Effects on Investment and Production

> The rapid and seemingly irresistible rise of the value-added tax (VAT) is probably the most important tax development of the latter twentieth century, and certainly the most breathtaking – Ebrill et al. [2001]

Since the inception of the first Value-Added Tax (VAT) system in 1954, over 150 countries have adopted a VAT system such that VAT revenue accounted for approximately 25% of total worldwide tax revenue by 2000 [Ebrill et al., 2001]. The rise of VATs has typically supplanted retail sales taxes (RST) and cascading turnover taxes (TT). Properly-designed VATs are superior to TTs and RSTs in part because a VAT leaves input prices undistorted while RSTs and TTs often create substantial distortions.[74] This reasoning dates back to Friedlaender [1967] and the canonical argument against tax systems that distort intermediate input decisions [Diamond and Mirrlees, 1971]. Nonetheless, despite the widely-shared agreement about the superiority of a VAT, the empirical literature evaluating the transition to VATs is fairly limited – in part because the rise of the VAT largely predated the increasing availability of high-quality business data.

In this paper, we help fill this gap by evaluating China's transition from a TT to a VAT (hereafter "B2V Reform") in 2012. The B2V reform was widely regarded as China's most significant tax reform in the last quarter century [Cui, 2014; Schenk et al., 2015].[75] A VAT on manufacturing firms was introduced in 1984, but all other industries (mostly services) remained under a TT. China began transitioning these remaining industries to the VAT in 2012. Approximately half of the previously-TT industries moved to the VAT in 2012 while the rest transitioned in 2016.[76] The staggered nature of the reform provides a quasi-experiment which we use to study the effects on firm outcomes.

The reform contained two parts. First, firms above the mandatory registration threshold (5 million CNY in revenue) were put into a regular VAT system. They could claim credit for the tax they paid on inputs, and issue VAT invoices to their customers, which effectively reduced the tax wedge on both their inputs and outputs. Capital inputs experienced the largest decrease because the tax rate applied to them is 17%, and therefore the ability to claim credit for that tax paid

[74] The RST in the U.S. is estimated to tax approximately 40% of business inputs.
[75] The VAT has been the largest source of tax revenues in China, while the BT, before it was replaced by the VAT, was the largest source of tax revenue for sub-national governments.
[76] A small group of industries transitioned in 2013-2015 as well.

caused a 17 percentage point (p.p) reduction. Second, firms below the registration threshold were put into a "simplified VAT" regime. They could not claim credit for tax paid on inputs, but received a reduction in the effective tax charged on outputs.

To study firm outcomes, we leverage detailed tax return and financial statement data from one large province. This data has the advantage that it contains firms of all sizes and from all industries. In contrast, the commonly-used National Bureau of Statistics (NBS) survey of industrial firms excludes all privately-owned service sector firms (the target of the reform) and all small and medium-sized firms.

The reform was predicted to (a) increase total output by improving production efficiency, specifically by (b) removing distortions in the input mix that and eliminating the incentive to inefficiently vertically integrate in order to avoid tax cascading, and (c) stimulate an especially strong increase in fixed asset purchases which experienced a much larger tax rate reduction than non-capital inputs. Empirically, we find limited effects of the reform on total firm output and non-capital inputs, but substantial increases in fixed assets. The increase in fixed assets in was concentrated in transportation and electronics. Buildings and structures, in contrast, did not see a change, consistent with real property remaining under the BT until 2016. Finally, we examine outsourcing (the opposite of vertical integration) in two ways. First, outsourcing would lead to reductions in labor and capital costs relative to total business costs, a prediction which we test, and do not find evidence of. Second, a rise in outsourcing may manifest through a rise in firm entry. Here, we find a substantial increase in new firm registrations in the treatment group relative to the control group, although view the result suggestive, not definitive.

To our knowledge, this is the first study of the B2V reform in China using tax return data covering a wide range of firms of different sizes. Li and Wang [2020] study listed companies, and find an increase in sales and input purchases. Similarly, Liu and Mao [2019] and Chen et al. [2019] both document a substantial increase in investment caused by a reform that culminated in 2009 which allowed VAT firms (manufacturing and wholesale) to claim input credit for tax paid on fixed asset purchases. In comparison, the B2V reform we study is (i) broader, as input credit became available to new regular VAT taxpayers for all inputs subject to the VAT, and (ii) affected not only the structure of business costs but also product prices. These changes are more typical of reforms in other countries that replace TTs with the VAT.

A substantial portion of the recent empirical VAT literature focuses on purported administrative properties of the VAT [Pomeranz, 2015; Waseem, 2018; Fan et al., 2018]. By contrast, our paper returns to the classic policy literature on the VAT, namely the efficiency gains that accrue by replacing turnover taxes with the VAT. Hoseini and Briand [2020] and Smart and Bird [2009] similarly evaluate the effects of transitioning from a sales tax to a VAT in Indian states and Canadian provinces, respectively.

5.1 Institutional Background

This section describes the institutional setting and policy reform relevant for our empirical strategy.

5.1.1 The Transition from Business Tax to Value-Added Taxes (B2V Reform)

The VAT applies to the sale of all goods except for intangible and immovable properties, as well as to the provision of processing, repair and replacement services. The BT was a tax on business gross receipts including the provision of services and transfers of intangibles and immovable properties, and applied to the non-VAT sectors. The BT was purely a TT: businesses in the BT regime could not claim credit for VAT or BT that was charged on their input purchases, and likewise, VAT firms could not claim credit for BT that was charged on their inputs. In this respect, the BT resembles RSTs in the United States, as well as TTs that were collected in many countries before the VAT was introduced to them [Ebrill et al., 2001; Schenk et al., 2015].

The B2V reform was introduced gradually through pilot sectors and regions from 2012 to 2016, a process by which the government tried to limit the initial impact of the reform to build political consensus [Cui, 2014]. The first set of industries ("2012 B2V" industries) were selected for the transition starting in 2012: Shanghai began its reform on January 1, while eight other provinces were chosen in July 2012 to begin the implementation in the last month of 2012. The same reform for the 2012 B2V industries was extended nationwide in August 2013. The reform extended to a few minor industries at different times in 2013 and 2014 ("2013-4 B2V" industries). The remaining BT industries transitioned to the VAT in May 2016 ("2016 B2V" industries).

Table 5.1 summarizes the sectoral sequence VATs introduction. The 2012 B2V industries comprised mostly the following: transportation and logistics (excluding railway), leasing (financing or operating), and a range of business services including R&D, licensing, IT, advertising, legal, accounting, and management services. They generated more than 15% of total BT revenue between 2009 and 2011. The 2013-4 B2V industries, comprising broadcasting, railway, postal and telecommunication services, generated only 4.3% of 2009-2011 BT revenue. The 2016 B2V industries included real estate (26% of BT revenue), construction (24% of BT revenue), financial and insurance services (15.6% of BT revenue) and most consumer services.

Under the VAT regime, firms above certain revenue thresholds are "regular VAT taxpayers": they are entitled to issue creditable VAT invoices, and can claim credit for VAT paid on input purchases. Firms below the threshold, unless they voluntarily register as regular VAT taxpayers, are "small-scale VAT taxpayers". They cannot claim credit for VAT paid on inputs, and must charge (since 2008) a 3% "simplified VAT" on their sales. For firms in the B2V reform sectors, the revenue threshold was annual sales of 5 million CNY ($800,000).[77]

[77] For industries already in the VAT system before the 2012 B2V reform, the registration threshold was CNY

Table 5.1: **Institutional Details of Chinese VAT**

Reform	Year	Sectors Affected	Rates	Registration Threshold	Simplified Rate
VAT Introduction	1984	Manufacturing			
Production-Type VAT	1994	VAT expanded to all goods except intangibles and immovable property	General Rate: 17% Exports: 0% Food: 11%	Manufacturing: 1,500,000 Wholesale: 1,800,000	6% (industrial) 4% (commercial)
Consumption-Type VAT	2004-2009	Fixed assets become creditable		Manufacturing: 500,000 Wholesale: 800,000	3%
B2V Reform	2012-2016	Services moved from BT to VAT	11% for traditional services (transportation, construction, telecom) 6% for modern services (R&D, IT, logistics, cultural) 17% leasing	Services: 5,000,000 Manufacturing: 500,000 Wholesale: 800,000	3%

Note: This figure illustrates the matrix of VAT and BT policies over time culminating in the 2012 reform.

The "simplified VAT" operates just like a turnover tax, except that it allows small-scale firms to issue creditable VAT invoices for the "simplified VAT" they collect. For sales to customers that can use such input credit (i.e., regular VAT taxpayers), there is effectively no VAT collected on sales, but any VAT paid by the firm on its input purchases are not credited.[78] During the period we study, simplified taxpayers could not issue invoices themselves but had to request that the tax authority issue VAT invoices on their behalf. The impact of this procedural requirement on invoice issuance among small-scale firms is unclear, but likely means that simplified VAT payers do not take full advantage of invoicing.

In summary, depending on whether a firm falls above or below the threshold in the new VAT regime, the reform broadly represents either (i) the combination of a reduction of the tax on sales and a reduction of the cost of input purchases (regular VAT taxpayers), or (ii) just a reduction of the tax on sales (simplified taxpayers).

Finally, a complex and unusual aspect of China's B2V reform is that different VAT rates applied to different goods and services. In designing the reform, China's policymakers substantially deviated from international VAT practice by creating different rates even for business (i.e. non-consumer) services: most services in the 2012 B2V industries were taxed at 6%, transportation was taxed at 11%, and leasing at 17%.[79] This was aimed at ensuring that the "tax burdens" on firms—interpreted as tax remittance—do not increase as a result of the reform [Cui, 2014]. Additionally, existing VAT industries, manufacturing in wholesale, continued to charge a 17% rate.

5.1.2 Voluntary Registration and Size-based Exemption

Several further features of China's VAT system are important for our research design. First, firms below the registration threshold may choose to be treated as regular taxpayers. During the period we study, once a taxpayer chooses to be regular taxpayer, it normally cannot revert to small taxpayer status. In our data, we do not observe whether a firm has regular taxpayer status, and therefore cannot identify whether a firm has voluntarily registered. However, while there are no published statistics about the prevalence of voluntary registration in China, the government has reported over many years that regular taxpayers represent fewer than 20% of the total population of VAT taxpayers in China.[80] This means that the rate of voluntary registration is bounded above at 20%–far lower than the rate (43%) reported for the UK [Liu and Lockwood, 2018]). Since regular taxpayer status is mandatory for firms when their revenues exceed the CNY 5 million threshold, the actual rate of voluntary registration is much lower— probably well below 10%. In our analyses below, we impute

500,000 or 800,000 (depending on sector) before 2016. The threshold was unified to CNY 5 million for all industries in 2016.

[78] For further details of the small taxpayer regime, see Chapter 14 of Schenk et al. [2015].

[79] The type of leasing within the 2012 cohort that's subject to the 17% rate is the leasing of tangible movable assets, and does not include real property. Tangible asset leasing is most concentrated in the 2-digit category of 71 (with multiple subcategories).

[80] For a recent news report to this effect, see `http://www.xinhuanet.com/fortune/2020-11/27/c_1126796078.htm`

the applicable regime — regular VAT or simplified collection applicable to “small taxpayers “ — to firms according to whether their revenue is above or below the registration threshold. We justify this imputation based on the relative infrequency of voluntary registration.

Prior to 2013, China exempted only sole proprietors with very low revenue from charging VAT or BT on their output. Beginning on August, 2013, this full exemption became available for VAT and BT taxpayers with monthly revenue of CNY 20,000 or less.Because micro-firms remit VAT or BT on a quarterly or even annual basis, many firms smoothed reported monthly revenue to benefit from the exemption. Firms with annual revenue lower than CNY 240,000 were thus generally exempt. This exemption threshold was lifted to CNY 30,000 a month (corresponding to annual income of CNY 360,000) beginning on October, 2014, where it remained to the end of our data coverage (2016).

5.2 Data and Sample

We use administrative tax return data from a large province that was among those selected to commence B2V reform in late 2012. The data set covers the period from 2010 to 2016, and comprises de-identified information from firms' tax registration records, annual corporate income tax (CIT) returns, income statements, and balance sheets. Several important features distinguish our data set from others used by researchers studying Chinese firms. First, in contrast to the Annual Survey of Manufacturers (often referred to as the National Bureau of Statistics Data), our data set covers firms in all industries. This is especially important for studying firms in the service sectors covered by the B2V reform. Second, our data set covers firms of all sizes, and allows us to examine the impacts of tax policies on the large population of small firms that would be excluded from other data sets.

Table 5.2 shows the number of firms observed in 2012 in each of the 2012 B2V, 2016 B2V, and Already-VAT groups.[81] The first two are split according to the the turnover tax (BT) rate they faced before their respective transitions to the VAT. The largest industries in the 2012 B2V are rental and business services; science research and technology; telecommunications, software and IT; and transportation and logistics. Most of this group faced a 5% turnover tax rate before the transition to VAT. The 2016 B2V group comprises a wider cross-section including construction, financial services, real estate, hospitality, in addition to rental and business services. The entirety of this group faced a 5% BT rate before the transition, with the notable exception of construction firms.

Sample Selection: We make the following sample restrictions to construct our analysis sample. First, we exclude transportation and logistics firms because they were subject to special and complex provisions under both the BT and VAT regime.[82] Second, we restrict to firm-year observations with

[81] Excluded are three sets of small industries that are mostly exempt from the BT and VAT: entertainment, public administration, and health and social work.

[82] Transportation was an industry where subcontracting was common, and the BT applied only on net revenue (net

Table 5.2: **Number of Firms in 2012 per Industry and Business Tax Rate**

	2012 B2V Firms		2016 B2V Firms		Already-VAT
Pre-VAT Turnover Tax (BT) Rate:	3%	5%	3%	5%	NA
Agriculture, Natural Resources	0	0	0	0	471
Construction	0	0	17314	0	0
Energy and Utilities	0	0	0	0	379
Financial Services	0	2	0	823	0
Hydrolics Environment	0	33	0	280	0
Hospitality	0	0	0	2274	0
Manufacturing	0	0	0	0	29467
Real Estate	0	0	0	8717	0
Rental and Business Services	0	10127	0	13237	0
Residential Services	0	0	0	6804	322
Science Research Technology	0	3010	0	1207	0
Telecommunication Software IT	157	1706	0	229	0
Transportation and Logistics	5220	1159	8	0	0
Wholesale and Retail	0	0	0	0	19398
Total	5377	16037	17322	33571	50037

Notes: This table shows the number of firms in 2012 in each aggregated industry code separated by the BT turnover tax rate the industry faced before the B2V reform. Excluded are three sets of small industries that are mostly exempt from the BT and VAT: entertainment, public administration, and health and social work.

positive total revenue and costs in order to remove inactive firms. Third, we keep only firms that registered in 2012 or earlier.[83] Fourth, we remove firms that had less than 360,000 in revenue averaged over 2010 to 2012. The 360,000 threshold corresponds to the full exemption threshold instituted for both the VAT and BT in 2014.[84]

Key Variables: We rely mostly on observations from CIT returns, as opposed to financial statements, since the latter only began being reported in 2012. Most importantly are the following: business revenues[85] and input cost variables (A100000 schedule), fixed assets reported at original cost on the depreciation return (A105080 schedule), and total wage expense (A105000 schedule). Costs are reported in the following three categories: (a) cost of goods and (b) business expenses, which approximately correspond to variable and fixed costs, respectively, and (c) management expenses. We construct total costs by summing the three categories together. Wages are supposed

of contracting expenses) as opposed to gross revenue. Transportation firms also enjoyed the privilege of issuing VAT invoices (at 7%) to customers that were VAT taxpayers and that could claim input credit. These special rules were reflected in transition rules during the B2V reform.

[83] In our data, 2012B2V firms that registered with tax authorities after the the 2012 reform are not present in our CIT returns. We apply this same restriction to the 2016B2V group for consistency.

[84] Approximately 30% of the firms cut by this restriction reported revenue above 360,000 in 2016.

[85] Under Chinese accounting rules, BT taxpayers reported revenue gross of BT, and BT payable is reported separately as a cost. When the BT was replaced by a VAT, revenue for accounting purposes does not include VAT. Therefore, to compare revenues before and after the reform for the treatment group, pre-reform revenue needs to have BT netted out. We apply this net-of-turnover tax definition to the control group as well.

to be apportioned to each of the three categories according to the purpose of the labor. The wage expense reported on the A105000 captures these combined labor expenses.

Table 5.3 reports descriptive statistics from 2012 for both reform groups in the analysis sample. Firms in the 2012 B2V group are substantially smaller than the 2016 B2V groups, as evidence by revenue and assets[86]. 44% of the 2016 B2V firms were above the 5 million registration threshold, as opposed to 23% in the 201 B2V group. 2012B2V firms are also younger, with 59.5% of them entering the tax registry between 2010 and 2012, and consistent with this, exhibit greater median revenue growth during that period. Finally, a substantial number of firms in both groups report making negative profits — 27% of firms report zero taxable income, while the average profit margin (profit over revenue) is negative.

Table 5.3: **Descriptive Statistics for Analysis Sample**

	2012 B2V Industries			2016 B2V Industries		
	Mean	Median	N	Mean	Median	N
Revenue 1000s	7899	1593	5697	37033	3662	23378
Total Cost 1000s	7383	1699	5697	34466	3712	23378
Total Assets 1000s	13316	1420	5697	100455	5527	23378
Fixed Assets 1000s	2456	44	5697	6284	127	23378
Taxable Income 1000s	654	20	5697	2394	50	23378
Fraction In Tax Losses	.275	0	5697	.272	0	23378
Profit / Revenue	-.121	.005	5697	-.115	.01	23378
Variable Cost Share	.539	.64	5697	.64	.797	23378
Fixed Cost Share	.098	0	5697	.083	0	23378
Present in 2016	0	0	5697	0	0	23378
Above 5 Million Rev	.234	0	5697	.441	0	23378
Revenue Growth	2.74	.247	4029	3.007	.143	17122
Wages / Total Costs	.139	0	5697	.124	0	23378
Fixed Assets / Total Costs	.294	.024	5697	.466	.027	23378
Cash Holdings / Total Assets	.37	.268	5519	.265	.122	22907
Claimed Interest Deduction	.061	0	5697	.133	0	23378
Entered Between 2010 2012	.595	1	5697	.446	0	23378
Age	5.648	3	5697	7.657	4	23378
State or Collectively Owned	.029	0	5697	.055	0	23378

Notes: This table shows descriptive statistics for 2012 and 2016B2V firms. All statistics use 2012 observations unless otherwise stated. Total assets, fixed assets, taxable income, and business revenue are reported in 1000 CNY. Firms that registered for tax purposes after October 2012 are excluded.

[86] Total Assets are as reported on financial statements and include intangible assets.

5.3 Effect of the Reform on Effective Tax Rates

Given the VAT rate differentiation, the co-existence of the BT and VAT, and the presence of a simplified VAT system for small scale firms, businesses face a complex set of tax rates on their inputs and outputs. To understand how tax rates vary across industries, this section estimates the average input and output tax rates before and after the 2012 reform. Appendix D contains the full explanation of this calculation. Below we overview the key components and results.

Consider firm i in industry j selling to customer c. The tax on this transaction depends on three parameters: (1) the statutory tax rate on the good or service being sold, (2) VAT-status of the customer, and (3) VAT-status of the seller. For each industry j, we therefore need to know who they buy from and sell to. For this, we use information from nationwide input-output tables in 2012 to estimate the fraction of each industry j's inputs and outputs flowing to and from other industries. Because the ability to issue VAT invoice and credit VAT paid differs between simplified and regular VAT payers, we also need to estimate the fraction of total input and output in each industry that derives from above- and below-scale firms. For this, we use the business revenue from our sample of firms. Finally, we assign the VAT and BT rates to firms based on the four-digit industry code reported in our taxpayer registry.

Table 5.4 shows the estimated average tax rates for above and below threshold firms in each group of industries.

Input Taxes: Before the reform, both groups faced a 9.8% tax on their inputs, on average. Following the 2012 reform, the input tax for above-threshold 2012 B2V firms dropped to nearly zero, reflecting their newfound ability to claim credit for tax paid on inputs. In contrast, for below-threshold firms, the input tax drop by about .6 p.p in both reform groups.

Output Taxes: Before the reform, the service industries faced approximately a 5% tax on their outputs — the BT rate was 5% in the 2012B2V group, and either 3% or 5% in the 2016B2V group. When the 2012 B2V group moved to the VAT, both above- and below-threshold firms' output tax rates dropped to .8 p.p and 1.9 p.p, respectively, reflecting their newfound ability to issue VAT invoices to customers, which effectively mollifies the tax on the transaction. The rate did not drop to zero because a segment of the economy still did not have the ability to credit the tax paid (firms still in the BT system and below-threshold VAT firms). Finally, the output tax rate remained the same for 2016 B2V firms.

There are two caveats. First, during the period we study, refunds for excess input credits were not allowed in connection with domestic sales. VAT refunds were only given for exports. If firms were in a position of excess input credit, they would have to offset that amount against VAT liabilities in the future. The inability to refund can strain business cash flow (and financially taxes firms as it forces them to lend interest free loans to the government). And therefore, the tax rate calculations for above-threshold firms in Table 5.4 likely over-state the benefits of the new tax system, particularly

Table 5.4: **Average Effective Input and Output Tax Rates**

Panel A: Below Threshold Firms						
	Input Tax			Output Tax		
	Before	After	Change	Before	After	Change
2012 B2V	0.098	0.092	-0.006	0.050	0.008	-0.042
2016 B2V	0.094	0.086	-0.007	0.045	0.045	0.000

Panel B: Above Threshold Firms						
	Input Tax			Output Tax		
	Before	After	Change	Before	After	Change
2012 B2V	0.098	0.008	-0.091	0.050	0.019	-0.031
2016 B2V	0.108	0.102	-0.006	0.042	0.042	0.000

Notes: This table shows effective input and output tax rates, separately for firms above and below the registration threshold, averaged within the 2012 B2V industries 2016 B2V industries.

given the propensity for firms to be loss-making (see Table 5.3).[87] Second, as described in Section 5.1, simplified VAT payers likely faced barriers to issuing VAT invoices. As a result, the output tax reductions Table 5.4 for these firms is over-stated.

A final consideration is that the average rates in Table 5.4 hide heterogeneity that bears on the subsequent analysis. Goods, as opposed to services, were largely under the VAT regime before the reform and subject to the 17% VAT rate. Purchasing firms in 2012B2V industries faced the entire 17% before the reform, but after the reform, when they gain the ability to claim credit for VAT paid, that tax rate effectively dropped to zero. This aspect of the reform incentivizes purchases of capital goods in particular.

5.4 Empirical Strategy

We compare outcomes across the 2012 and 2016 reform industries to identify the effects of the reform on firm outcomes. The first part of the analysis pools together all firms above the 360,000 threshold. This corresponds to the policy effects of moving from a TT to a real-world VAT that contains both regular and simplified components. We then split this group into above and below 5,000,000, based on firms' average revenue between 2010 and 2012, to explore mechanisms and to interpret results. Under this approach, treatment effects are considered intent-to-treat since, as Figure D.1 shows, about 20% of firms cross the threshold (in either direction) after the reform.[88]

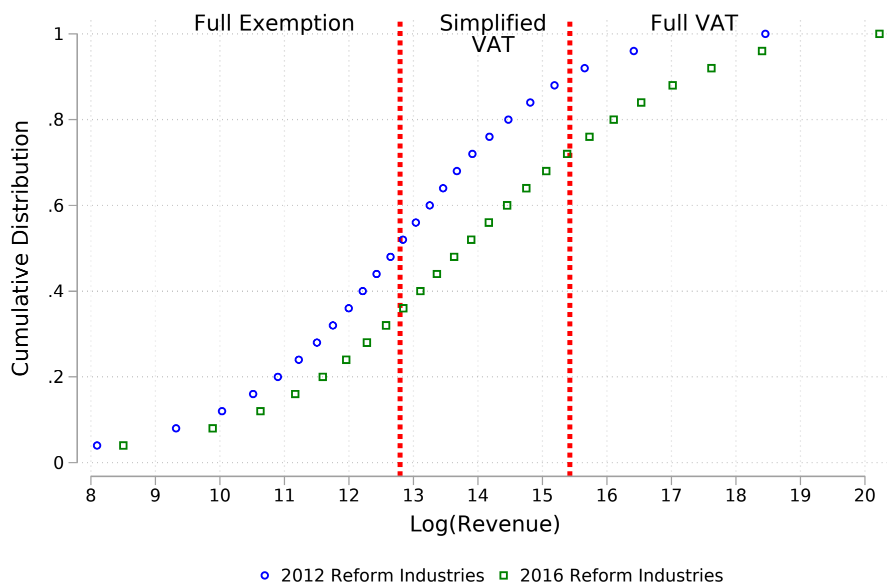
Figure 5.1 illustrates the cumulative distribution of firm revenue (in 2012) around the thresholds.

[87] If a firm is in a negative profit position on the corporate income tax, they are more likely to have excess input credit, particularly firms with low labor expenses, and firms undertaking large investments.

[88] Figure D.2 shows a minor degree of bunching below the 5,000,000 million threshold, suggesting a minor degree of self-selection in the simplified and regular VAT schemes.

The first vertical line indicates 360,000 in annual revenue, which corresponds to the full-exemption for micro-firms from both the BT and VAT who we exclude from the analysis. The second vertical line denotes the 5,000,000 VAT registration threshold, above which firms in the VAT regime must register as regular VAT payers. Firms in the middle, if in a VAT industry, are assumed to be simplified payers.[89]

Figure 5.1: **Cumulative Distribution Functions by Reform Group**



Notes: This figure plots the cumulative distribution functions of 2012 revenue for the 2012 and 2016 B2V groups. The second vertical line denotes the mandatory registration threshold (5,000,000 CNY) for the full VAT system, above which firms are required to register as regular VAT taxpayers. The first line denotes the full exemption threshold, below which firms are exempt from charging any tax on output. Firms between both lines fall under imputed to the simplified VAT regime.

To visualize the empirical design, we first estimate dynamic effects on firm-level outcomes from the following model:

$$y_{it} = \sum_{\tau=2010}^{2015} \theta_\tau \mathbb{1}[t = \tau] \times D_i + \alpha_i + \alpha_t + \alpha_a + \epsilon_{it} \tag{5.1}$$

where α_i and α_t are firm and year fixed effects, and D_i is a dummy equal to 1 if the firm belongs to the 2012 B2V group and 0 if they belong to the 2016 B2V group. We also control for firm age fixed effects α_a. As shown in Table 5.3, firms entry into tax registration was quite prominent during the 2010 to 2012 period. Controlling for age fixed effects helps capture any differences driven by differential entry between treatment and control industries. Each coefficient θ_τ measures the change

[89]While less than 20% of firms are above the 5,000,00- threshold, they account for over 95% of aggregate firm revenue.

in the outcome variable y_{it} for treated firms relative to control firms in the τ-th year before or after the 2012 reform.[90] θ_{2012} is normalized to be zero. We also compute average effects by estimating a static version of equation (5.1):

$$y_{it} = \theta D_i \times P_t + \alpha_i + \alpha_t + \alpha_a + \epsilon_{it} \tag{5.2}$$

where P_t is a dummy equal to 1 for years 2013 to 2015.

There are two main identifying assumptions. The first is a partial equilibrium notion: that the treated and control firms' outcomes would have trended similarly in the absence of the policy change. Parallel pre-reform trends will partially validate this assumption.

The second is a general equilibrium notion: the reform effects on the treated group do not contaminate the control group. This is unlikely since both treatment and control industries do a substantial amount of business-to-business transactions. An increase in economic activity by treated firms will, to some extent, increase demand for control-group services. The DiD estimator will therefore be a lower bound on the true effect of economic activity. However, the effect on restructuring of production, such as via outsourcing, would only occur within the treatment group. Similarly, the 17 p.p decline in tax on fixed asset purchases in the treatment group is likely to dwarf minor spillovers to control group fixed asset demand.

5.4.1 Outcome Variables: Investment, Output, Costs, and Input Mix

Asset Growth: We measure investment based on changes in asset stock. To relate the changes to investment expenditure, we assume that assets accumulate according to the following identity:

$$K_t = I_t + K_{t-1} - S_t \tag{5.3}$$

K_t denotes fixed assets measured at original cost at the end of year t, I_t denotes new asset purchases made in t,and S_t denotes asset dispositions in t, both valued at the original purchase cost. We rely on original cost measures because these are reported on tax returns beginning in 2010, whereas asset stock measured net of accounting depreciation is only available beginning in 2012.

We adopt $Ln(K_t)$ as our main outcome variable. Because firm fixed effects are included in equation 5.2, the estimator of θ is based on within-firm changes: $Ln(K_{i,t}) - Ln(\bar{K}_{i,b})$, where $Ln(\bar{K}_{i,b}) = \frac{1}{T}\sum_t Ln(K_{i,t})$. This approximates the growth rate of the asset stock relative to the firm's mean: $\frac{K_{i,t}-\bar{K}_i}{\bar{K}_i} = \frac{I_{i,t}-\bar{I}_i}{\bar{K}_i} - \frac{S_{i,t}-\bar{S}_i}{\bar{K}_i}$. If asset dispositions are orthogonal to the reform, then the identifying variation rests solely on $\frac{I_{i,t}-\bar{I}_i}{\bar{K}_i}$ which is the investment rate. If asset dispositions are affected by the reform, then θ is a downward-biased estimate of the effect on investment. For example, if firms replace existing asset stock with new purchases because of the reform, then both

[90] Standard errors are clustered at the four digit industry-level. There are 54 treated clusters and 86 control clusters.

$S_{i,t}$ and $I_{i,t}$ increase and estimated θ will be smaller than the effect on $I_{i,t}$. We therefore view our estimates as lower bounds on the true effect on the investment.

Output: We use total revenue to measure output. We remove from total revenue the taxes charged on output, such that it reflects output quantity times the net-of-tax price (producer prices). By reducing the output tax wedge, the reform is expected to weakly increase producer prices, and if so, then the treatment effect on revenue would capture this price effect in addition to quantity expansions.

Non-Capital Inputs: Non-capital inputs are measured as the total expenses listed on CIT returns (which include both material inputs and labor expenses).[91] We measure total costs net of tax paid on inputs, and therefore at producer prices.

Wages: We isolate the effect on labor inputs using total wages. This variable should be considered cautiously however. Figure D.3 shows that before 2014, the majority of firms reported zero wages, then in 2014 this dropped to less than 10%.

Measures of Vertical Integration: We measure outsourcing in two ways. First, wage expenses as a fraction of total costs, which would decline as firms substitute in-house labor for outsourced services. Second, physical capital relative to total costs, which too would decline if the newly-outsourced services require capital to produce.

5.5 Results

5.5.1 Baseline Results

Figure 5.2 plots the coefficients θ_τ from equation (5.1), where $\tau \in (2010, ..., 2015)$, for each outcome. Table 5.5 shows the corresponding average effects from equation (5.2). The first panel shows results for the entire sample; the second panel results for simplified VAT payers; and the third panel results for regular VAT payers.

In both the combined sample and both sub-samples, there is no evidence of output or inputs rising, suggesting no change in relative change firm activity. In the combined sample, the estimated treatment effect is a statistically insignificant .4% increase in revenue and .2% in total costs. The treatment effects are similarly small for the simplified and regular taxpayer samples.

Turning to fixed assets, Panel (c) of Figure 5.2 shows a strong and relatively immediate increase in assets for regular VAT firms. Table 5.5 reports an average increase of 10.5%. This is consistent the 17 p.p reduction in the tax paid such assets. And, again, 10.5% is certainly a lower bound on the true effect. In subsection 5.5.2 we examine which types of assets firms invested in. Below-threshold firms, in contrast, exhibit only a statistically insignificant 2.9% increase, consistent with them continuing to face the 17% rate on asset purchases.

[91] Costs on tax returns are exclusive of tax.

It is perhaps puzzling that capital purchases increased while overall output and non-capital inputs did not. One explanation is that firms upgraded old equipment without changing the scale of operations, and with the upgrades having limited productivity effects.

Turning to the proxies for outsourcing — Wages / Input Costs and Fixed Assets / Input Costs — we do not find statistically significant effects except in the combined sample where wages increase relative to costs (the opposite of outsourcing). Among above-threshold firms, where outsourcing is predicted, we find no evidence of it. Opportunities for outsourcing may simply be limited. In subsection 5.5.4, we will return to outsourcing when discussing new firm entry.

Table 5.5: **Difference-in-Differences Results**

Pooled Sample

	Ln Revenue	Ln Total Cost	Ln Fixed Assets	Ln Wages	Wages/Costs	Capital/Costs
Treated x Post	0.004	0.002	0.068^{**}	0.037	0.019^{**}	-0.014
	(0.082)	(0.072)	(0.032)	(0.033)	(0.009)	(0.040)
Treated Mean	14.50	14.57	12.84	13.04	0.16	0.36
Observations	141771	141771	98418	96262	141771	141771
Treated Firms	5652	5652	4232	4978	5652	5652
Control Firms	23907	23907	17933	20531	23907	23907

Simplified VAT Sample

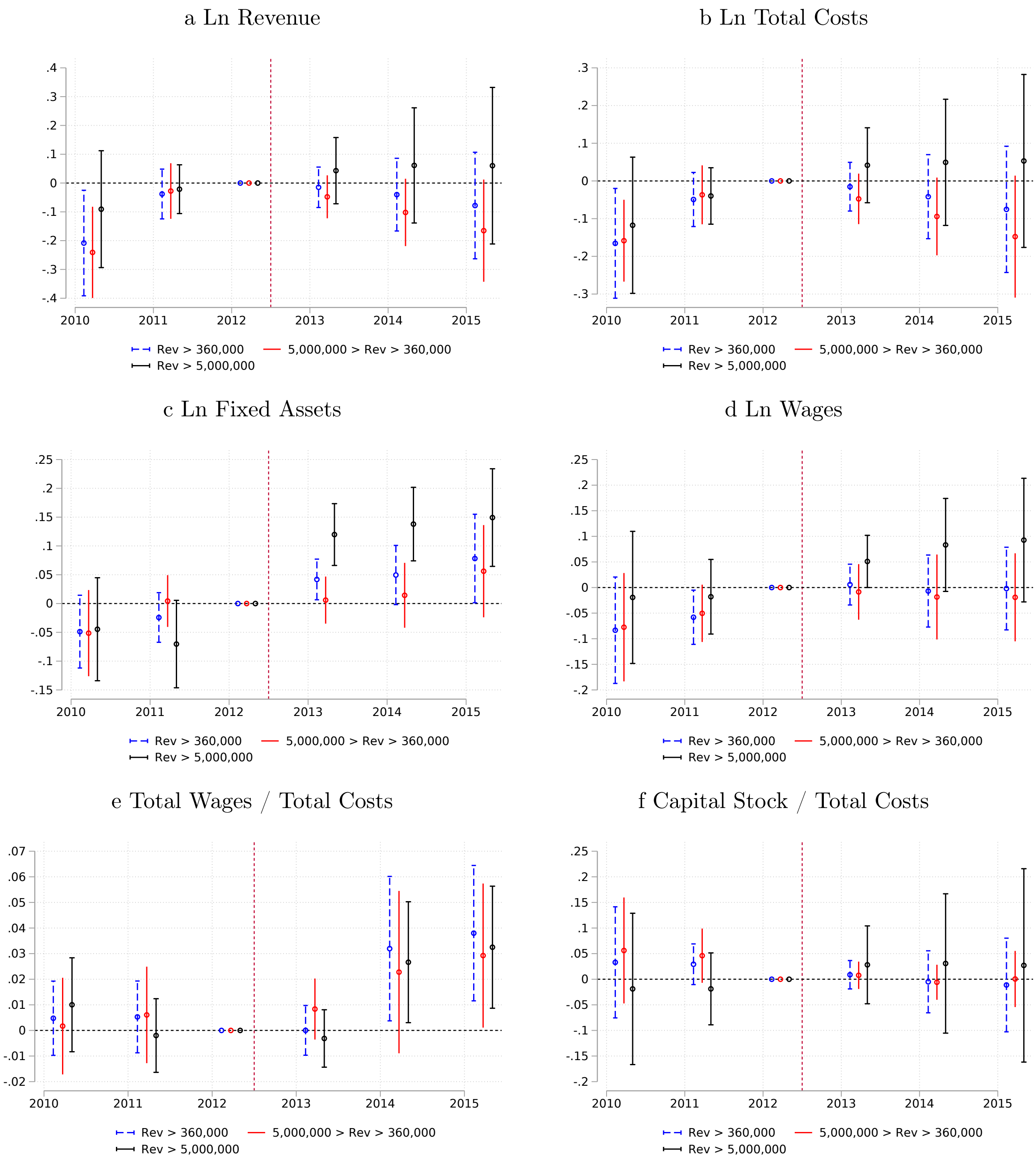
	Ln Revenue	Ln Total Cost	Ln Fixed Assets	Ln Wages	Wages/Costs	Capital/Costs
Treated x Post	-0.060	-0.059	0.029	0.019	0.010	-0.017
	(0.073)	(0.064)	(0.030)	(0.035)	(0.009)	(0.023)
Treated Mean	13.77	13.89	11.95	12.33	0.16	0.32
Observations	79990	79990	47053	51274	79990	79990
Treated Firms	4389	4389	3085	3796	4389	4389
Control Firms	13297	13297	8586	10887	13297	13297

Regular VAT Sample

	Ln Revenue	Ln Total Cost	Ln Fixed Assets	Ln Wages	Wages/Costs	Capital/Costs
Treated x Post	-0.076	-0.040	0.105^{***}	0.002	0.012	0.054
	(0.081)	(0.074)	(0.032)	(0.048)	(0.009)	(0.064)
Treated Mean	16.52	16.44	14.54	14.56	0.16	0.47
Observations	61706	61706	51293	44901	61706	61706
Treated Firms	1261	1261	1143	1177	1261	1261
Control Firms	10606	10606	9340	9635	10606	10606

Notes: This table presents difference-in-differences estimates from equation (5.2). Treated firms are those in the 2012 B2V industries, and control firms those in the 2016 B2V industries. Outcomes are defined in Section 5.4.1. All outcomes are winsorized at the 1 and 99 percentiles. Standard errors are clustered at the four digit industry code and are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 5.2: **The Effects of B2V Reform on Firm Outcomes (Pooled Sample)**



Notes: This figure plots event-study coefficient estimates as in equation (5.1). The treated group consists of firms in 2012 B2V industries. The control group consists of firms above 360,000 CNY in revenue (measured in 2012) in 2016 B2V industries. Outcomes are defined in Section 5.4.1. Standard errors are clustered at the four digit industry code. All outcomes are winsorized at the 1st and 99th percentiles.

5.5.2 Heterogeneity Across Asset Types

Chinese tax law sets out five types of assets: (1) production equipment, (2) furniture and tools, (3) structures, (4) transportation, and (5) electronics. Firms report the original cost of each on their tax returns for assets still in use. Figure 5.3 illustrates the average asset composition among firms in the analysis sample. For each asset type k, we calculate $\frac{K_{i,t,k}}{K_{i,t}}$, the share of firm i's total fixed asset stock accounted for by type k, then calculate the average across firms. Electronics account for 40% of total fixed assets on average in the treatment group, consistent with these firms comprising business services, science and technology, and telecommunications firms. Second most prominent is transportation (despite transportation industries being excluded). The control group is similar, but with less slant towards electronics, and a greater share of production equipment.

To investigate which types of fixed asset underlie the positive treatment effect in Table 5.5, we use $\frac{K_{i,t,k}}{K_{i,b}}$ as the outcome in equation 5.2, where $K_{i,b}$ is firm i's pre-reform average total fixed asset stock. This has the advantage that $\sum_k \frac{K_{i,t,k}}{K_{i,b}} = 1$, making the magnitude of θs comparable across asset classes.

For above-threshold firms, furniture, transportation, and especially electronics drive the investment response. There is no effect on structures, consistent with the sale and purchase of real property remaining subject to the BT until 2016. Among below-threshold firms, there are offsetting effects — production equipment, transportation, and structures decreased while electronics increased substantially.

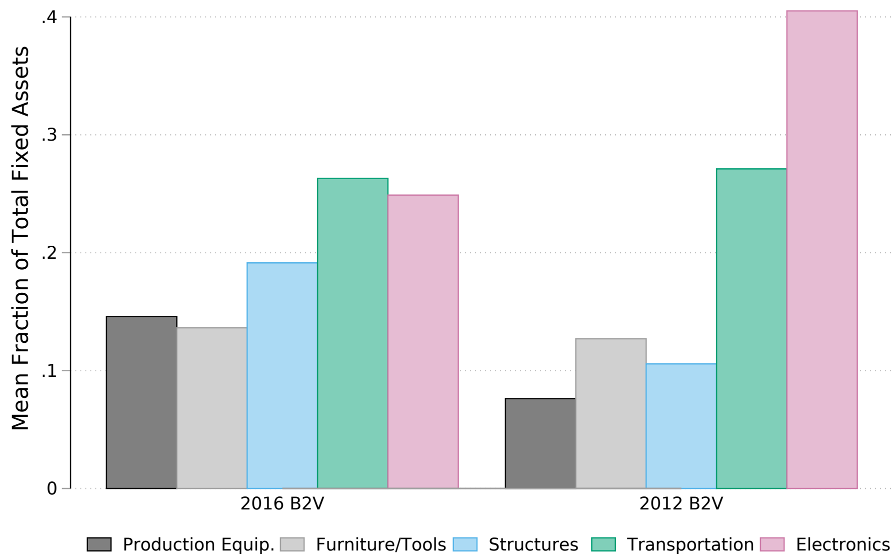
Table 5.6: **Results by Asset Type**

Simplified VAT Sample					
	Production	Furniture	Structures	Transportation	Electronics
Treated x Post	-0.041**	-0.029	-0.064**	-0.067	0.198***
	(0.019)	(0.021)	(0.030)	(0.142)	(0.055)
Treated Mean	0.07	0.13	0.05	0.27	0.47
Observations	50636	50636	50636	50636	50636

Regular VAT Sample					
	Production	Furniture	Structures	Transportation	Electronics
Treated x Post	0.016	0.041*	0.151	0.158**	0.403***
	(0.035)	(0.022)	(0.125)	(0.076)	(0.101)
Treated Mean	0.10	0.10	0.22	0.26	0.30
Observations	54327	54327	54327	54327	54327

Notes: This shows difference in difference estimates for each asset type, where the outcome is $K_{i,t,k}/K_{i,b}$, where $K_{i,t,k}$ is the firm's asset stock of type k in year t and $K_{i,b}$ is firm i's average pre-reform total asset stock. Outcomes are winsorized the the 1st and 99th percentiles. Standard errors are clustered at the four digit industry code and are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure 5.3: **Asset Composition**



Note: This figure shows the average fixed asset composition among the 2012B2V and 2016B2V groups. There are five asset types under Chinese tax law: (1) production equipment, (2) furniture, (3) buildings and structures, (4) transportation, and (5) electronics.

5.5.3 Heterogeneity Across Firms

We next examine two dimensions of heterogeneity across firms. First, labor-intensive firms benefit less from a reduction taxes paid on physical inputs, which leads to the natural prediction that *above-threshold* labor-intensive firms are less affected by the reform. We test this prediction by defining a firm as labor-intensive (LI) if a firm's total wage bills scaled by total costs (inclusive of the wages) is above the median at the time of the reform in 2012, and 0 otherwise.

Second, we examine heterogeneity by firm size. Cui et al. [2020] and Fan and Liu [2020] both find greater responsiveness to tax incentives among larger firms in China. The former suggest an information frictions mechanism, while the latter conjecture that smaller firms are simply less compliant with the tax system, and therefore less influenced by it. Regardless of the mechanism, both papers would predict greater reform effects on large firms. We define a large firm as whether they have total pre-reform assets above the median of their respective reform groups.

We jointly test these hypothesis by modifying equation (5.2) to include interactions with both indicators:

$$y_{it} = \alpha + \theta D_i P_t + \theta_{LI} D_i P_t \text{LI}_i + \theta_{Large} D_i P_t \text{Large}_i + \alpha_i + \alpha_{t,LI,Large} + \epsilon_{it} \tag{5.4}$$

Where year fixed effects ($\alpha_{t,LI,Large}$) are included for each subgroup. The coefficient θ_{LI} is predicted to be negative for above-threshold firms, and θ_{Large} is predicted to be positive for both above- and below-threshold firms. We include estimate the two interactions simultaneously because firm size is negatively correlated with labor intensity, making it important to control for each.

Table 5.7 shows the results. Opposite to predictions, θ_{LI} is statistically indistinguishable from zero for above-threshold firms. For below threshold firms, where predictions are ambiguous, θ_{LI} is again indistinguishable across outcomes except for a minor significant coefficient for total revenue. Consistent with Cui et al. [2020] and Fan and Liu [2020], large firms in the regular VAT sample show greater investment responsiveness, double that of the smaller firms.

Table 5.7: **Difference-in-Differences Heterogeneity**

Simplified VAT Sample

	Ln Revenue	Ln Total Cost	Ln Fixed Assets	Ln Wages	Wages/Costs	Capital/Costs
Treated x Post	-0.050	-0.040	0.090^{*}	0.101	0.003	0.037
	(0.068)	(0.065)	(0.050)	(0.093)	(0.021)	(0.026)
x Labor Intensive	0.073^{*}	0.063	-0.059	-0.095	0.004	-0.041
	(0.038)	(0.039)	(0.047)	(0.098)	(0.020)	(0.040)
x Large Firm	-0.066	-0.076	-0.015	0.033	0.014	-0.041
	(0.084)	(0.071)	(0.033)	(0.082)	(0.010)	(0.040)
Treated Mean	13.77	13.89	11.95	12.33	0.16	0.32
Observations	79990	79990	47053	51274	79990	79990

Regular VAT Sample

	Ln Revenue	Ln Total Cost	Ln Fixed Assets	Ln Wages	Wages/Costs	Capital/Costs
Treated x Post	-0.050	-0.035	0.092^{**}	0.066	0.032	-0.064
	(0.124)	(0.121)	(0.039)	(0.085)	(0.023)	(0.077)
x Labor Intensive	0.009	0.016	-0.030	-0.023	-0.028	0.089
	(0.104)	(0.099)	(0.058)	(0.094)	(0.025)	(0.081)
x Large Firm	-0.080	-0.018	0.119^{*}	-0.073	-0.002	0.230^{**}
	(0.101)	(0.099)	(0.072)	(0.062)	(0.012)	(0.108)
Treated Mean	16.52	16.44	14.54	14.56	0.16	0.47
Observations	61706	61706	51293	44901	61706	61706

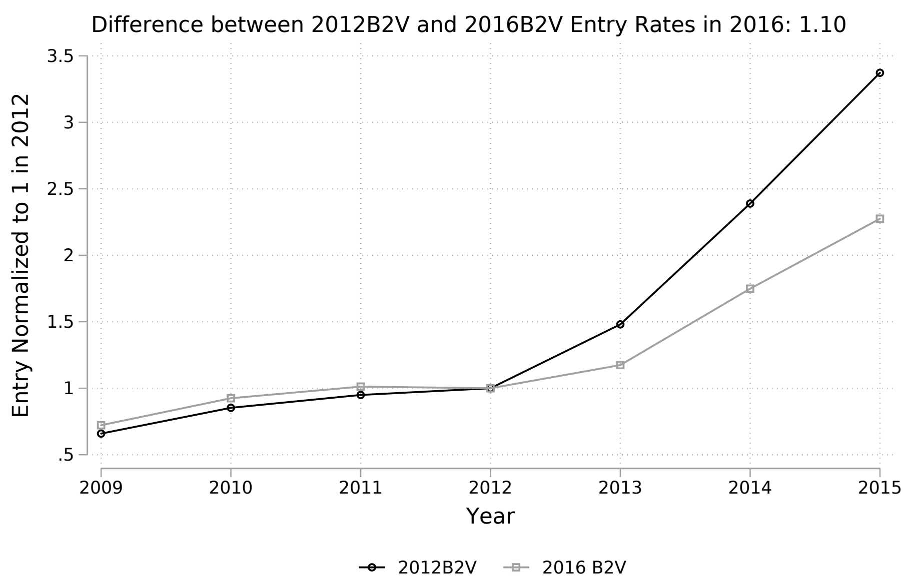
Notes: This table presents difference-in-differences estimates from equation (5.4). Treated consists of firms in 2012 B2V industries and control group consists of firms in 2016 B2V industries. Outcomes are defined in Section 5.4.1 and are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the four digit industry code and are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.5.4 Firm Entry

Increases in outsourcing may be accompanied by the creation of new firm entities. To examine firm entry, we draw on the firm taxpayer registry which contains a snapshot of all firms in 2017, and includes their data of registration. This is a much larger set of firms than we have CIT returns (which our analysis of firm outcomes is based on). This snapshot however excludes any firms that entered during the sample period but de-registered before 2017.

Figure 5.4 plots firm entry over time in the 2012B2V and 2016B2V groups. In each year, we count the number of entrants in each group, then divide by the number in 2012, so that entry is normalized to 1 in that year. There are clear parallel trends in entry before 2012, followed by a gradual departure starting in 2013 and increasing over time. By 2016, entry had doubled for the control group, but tripled for the treatment group, implying a substantial treatment effect, perhaps implausibly large. As it stands, there are no comparable estimates in the literature to benchmark against.[92] One explanation for the large effect, aside from outsourcing-driven creation of new firms, is that infra-marginal entrants influence the industry code they are assigned at registration time in order to put taxed under VAT rather than the BT. Further work is required to pin down the source this large effect.

Figure 5.4: **Firm Entry into the Taxpayer Registry**



Note: This figure plots firm entry into each industry group, normalized to 1 in 2012.

[92]The closest is an working paper abstract the reports increases in outsourcing in the marijuana industry in Washington state.

5.6 Conclusion

In this paper, we examine the effects of China's transition from a turnover tax to a VAT. Not only was this the largest tax reform in modern Chinese history, it was also a continuation of perhaps the biggest trend in worldwide tax systems since the 1940s. Despite the tremendous importance of the VAT, to date there has been very limited evidence on the effect of this phenomenon. Academics have been left to rely on cross-country time variation Ebrill et al. [2001], the experience of Canadian provinces [Smart and Bird, 2009], or the recent Indian transition [Hoseini, 2020]. Our paper builds on this nascent body of work.

We find a substantial increase in fixed asset investment due to the effective 17 p.p tax reduction on these goods. We however find no effect on firm scale (revenue). We also find no effect on firm input mix that would indicate an increase in outsourcing, suggesting a highly inelastic rate of substitution between in-house production and outsourced inputs, at least for the business service firms that comprise most of the reform group. In preliminary work, we also find a substantial increase in firm entry in the reform industries. In subsequent work, we will investigate the source of firm entry, and the apparent lack of changes in the input mix.

Chapter 6

Conclusion

The introduction of this thesis motivated the undertaking by appealing to the sheer scale of China's tax system, the fundamental differences relative to tax systems in developed nations, and the nascent state of the scholarly work studying China's fiscal state. To conclude, it is useful to instead highlight China's similarity to other contemporary emerging economies, and how the lessons in this thesis inform policy outside of China's borders.

Like China, most emerging economies rely more heavily on consumption and business taxes and are establishing VAT systems as the cornerstone of those taxes: Russia established a VAT system in the 1990s, India in the 2000s, while Brazil largely not yet made the transition. And in those emerging economies with new VAT systems, there is substantial room for reform. India's VAT introduction, for instance, was so complex that the ideal of production neutrality was no where in sight. The evidence on China's VAT reform (Chapter 4), therefore, is not only a historical curiosity, but bears continued policy relevance for many countries (including some Canadian provinces and the United States which still lack a VAT system).

Likewise, the implications of information frictions and a lack of tax expertise (Chapter 1) for governments' ability to enact new policies is likely not unique to the Chinese context. Imperfect take-up of tax incentives has been documented in other countries, such as Vietnam [Pham, 2019], and in the historical experiences of now-developed economies [Wales, 1966]. The Chinese experience with AD should caution against assuming that tax policies that work in places like the modern-day U.S. and U.K. will succeed in developing and emerging economies.

And finally, while China's social insurance system is unique (Chapters 2 and 3), it shares the common goal of with other emerging economies of establishing broad social insurance safety net in the face of substantial informality [Bird and Smart, 2014].

Bibliography

Aarbu, K. O. and Mackie-Mason, J. K. (2003). Explaining Underutilization of Tax Depreciation Deductions: Empirical Evidence from Norway. *International Tax and Public Finance*, 10(2003):229–257.

Abeler, J. and Jäger, S. (2015). Complex Tax Incentives. *American Economic Journal: Economic Policy*, 7(3):1–28.

Alfaro, L., Becerra, O., and Eslava, M. (2020). EMEs and COVID-19 Shutting Down in a World of Informal and Tiny Firms. *NBER Working Paper No. 27360*.

Alon, T. M., Kim, M., Lagakos, D., and Vuren, M. V. (2020). How Should Policy Responses To the Covid-19 Pandemic Differ in the Developing World. *NBER Working Paper 27273*.

Alstadsaeter, A., Bjorkheim, J. B., Kopczuk, W., and Okland, A. (2020). Norwegian and US Policies Alleviate Business Vulnerability Due to the COVID-19 Shock Equally Well. *NBER Working Paper 27637*, 42(4):1.

Auerbach, A. J. (1982). The New Economics of Accelerated Depreciation. *Boston College Law Review*, 23(5):1327–1355.

Bachas, P., Brockmeyer, A., Semelet, C., and Ungerer, C. (2020). The Impact of COVID-19 on Formal Firms: Evidence from Albania. *Macroeconomics, Trade & Investment Practice Notes*, (9):1–12.

Barrero, J. M., Bloom, N., and Davis, S. J. (2020). COVID-19 Is Also a Reallocation Shock. *Brooking Papers on Economic Activity*, June 25.

Bartik, A. W., Bertrand, M., Cullen, Z., Glaeser, E. L., Luca, M., and Stanton, C. (2020). The impact of COVID-19 on small business outcomes and expectations. *Proceedings of the National Academy of Sciences of the United States of America*, 117(30):17656–17666.

Bazel, P. and Mintz, J. (2019). Policy Forum: Is Accelerated Depreciation Good or Misguided Tax Policy? *Canadian Tax Journal*, 61:41–55.

Bennedsen, M., Larsen, B., Schmutte, I., Scur, D., Butera, L., Furman, J., Hassler, J., Gautier, P., and Mann, K. (2020). Preserving job matches during the COVID-19 pandemic: firm-level evidence on the role of government aid. (June).

Bird, R. and Smart, M. (2014). Financing Social Expenditures in Developing Countries: Payroll or Value-Added Taxes? In Frolich, M., Kaplan, D., Pages, C., Rigolini, J., and Robalino, D., editors, *Social Insurance, Informality, and Labor Markets*, chapter 13. Oxford University Press, Oxford.

Birinci, S., Karahan, F., Mercan, Y., and See, K. (2020). Labor Market Policies During an Epidemic. *Rederal Reserve Bank of St.Louis Working Paper 2020-024B*.

Bond, S. and Xing, J. (2015). Corporate taxation and capital accumulation: Evidence from sectoral panel data for 14 oecd countries. *Journal of Public Economics*, 130:15–31.

Bonomo, M., Brito, R. D., and Martins, B. (2015). The after crisis government-driven credit expansion in Brazil: A firm level analysis. *Journal of International Money and Finance*, 55:111–134.

Brockmeyer, A. and Bachas, P. (2020). Using administrative tax data to understand the implications of COVID-19 for formal firms.

Bruhn, M. (2020). Can Wage Subsidies Boost Employment in the Wake of an Economic Crisis? Evidence from Mexico. *Journal of Development Studies*, 56(8):1558–1577.

Cai, H. and Liu, Q. (2009). Competition and Corporate Tax Avoidance: Evidence from Chinese Industrial Firms. *The Economic Journal*, 119(537):764–795.

Chen, J., Cheng, Z., Gong, K., and Li, J. (2020a). Riding Out the COVID-19 Storm: How Government Policies Affect SMEs in China. *SSRN Electronic Journal*.

Chen, Z., Li, P., Liao, L., and Wang, Z. (2020b). Assessing and Addressing the Coronavirus-Induced Economic Crisis: Evidence From 1.5 Billion Business Transactions in China. *SSRN Electronic Journal*.

Chen, Z., Liu, Z., Serrato, J. C. S., and Xu, D. Y. (2020c). Notching R&D Investment with Corporate Income Tax Cuts in China. *American Economic Review*, pages 1–65.

Chen, Z., Zian, J., Zhikuo, L., and Carlos Suarez Serrato, J. (2019). Tax Policy and Lump Investment Behavior: Evidence from China's VAT Reform. *NBER Working Paper 26336*, 13(1):1689–1699.

Chetty, R., Friedman, J. N., and Saez, E. (2013). Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings. *American Economic Review*, 103(7):2683–2721.

Chetty, R., Friedman, J. N., and Stepner, M. (2020). How did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data. *NBER Working Paper 27431*.

Cooper, M. and Knittel, M. (2006). Partial Loss Refundability: How Are Corporate Tax Losses Used? *National Tax Journal*, 59(3).

Cui, W. (2011). Fiscal Federalism in Chinese Taxation. *World Tax Journal*, 3:455.

Cui, W. (2014). China's Business-Tax-to-VAT Reform: An Interim Assessment. *British Tax Review*, (5).

Cui, W. (2015). Administrative decentralization and tax compliance: A transactional cost perspective. *University of Toronto Law Journal*, 65(3):186–238.

Cui, W. (2021). *Administrative Foundations of the Chinese Fiscal State*. Cambridge University Press.

Cui, W., Hicks, J., and Xing, J. (2020). Cash on the Table? Imperfect Take-up of Tax Incentives and Firm Investment Behavior. *Working Paper*.

Dabla-Norris, E., Misch, F., Cleary, D., and Khwaja, M. (2019). The quality of tax administration and firm performance: evidence from developing countries. *International Tax and Public Finance*.

Deng, Y., Fang, H., Hanewald, K., and Wu, S. (2021). Delay the Pension Age or Adjust the Pension Benefit? Implications for Labor Supply and Individual Welfare in China.

Diamond, P. A. and Mirrlees, J. A. (1971). Optimal taxation and public production I: Production efficiency. *The American Economic Review*, 61(1):103–122.

DiNardo, J., Fortin, N. M., and Lemieux, T. (1996). Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64(5):1001.

Ebrill, L., Keen, M., and Summers, V. (2001). *The Modern VAT*. International Monetary Fund.

Edgerton, J. (2010). Investment incentives and corporate tax asymmetries. *Journal of Public Economics*, 94(11-12):936–952.

Edgerton, J. (2012). Investment, Accounting, and the Salience of the Corporate Income Tax. *NBER Working Paper*.

Fan, H., Liu, Y., Qian, N., and Wen, J. (2018). The Dynamic Effects of Computerized VAT Invoices on Chinese Manufacturing Firms. *CEPR Discussion Papers*.

Fan, Z. and Liu, Y. (2020). Tax Compliance and Investment Incentives: Firm Responses to Accelerated Depreciation. *Journal of Economic Behavior and Organization*, 176:1–17.

Fang, H. and Feng, J. (2018). The Chinese Pension System. *NBER Working Paper 25088*.

Feng, J. (2013). The Incentive of Participation in Urban Social Insurance System in China: A Study Based on Manufacturing Firms. *Economic Research Journal*.

Feng, J. and Faqiang, Z. (2019). 70 Years of New China Pension Insurance: Experience, Problems and Prospects. *Social Security Research*, (6).

Forsling, G. (1998). Utilization of tax allowances. *Finnish Economic Papers*, 11(2).

Frazier, M. W. (2010). *Socialist Insecurity*. Cornell University Press, Ithaca, 1 edition.

Friedlaender, A. F. (1967). Indirect Taxes and Relative Prices. *The Quarterely Journal of Economics*, 81(1):125–139.

Ganong, P., Noel, P., and Vavra, J. (2020). US Unemployment Insurance Replacement Rates During the Pandemic. *Journal of Public Economics*.

Gao, Q. and Rickne, J. (2014). Firm Ownership and Social Insurance Inequality in Transitional China: Evidence from a Large Panel of Firm-Level Data. *European Journal of Social Security*, 16(1):2–25.

Gao, Q. and Rickne, J. (2017). Inequality in Social Insurance Participation and Generosity: Do Firm Characteristics Matter? *Social Policy and Administration*, 51(September):755–775.

Ghosal, V. and Loungani, P. (2000). The differential impact of uncertainty on investment in small and large businesses. *Review of Economics and Statistics*, 82(2):338–343.

Goodspeed, T., Martinez-Vazquez, J., and Zhang, L. (2013). Do Companies View Bribes as a Tax? Evidence on the Tradeoff between Corporate Taxes and Corruption in the Location of FDI. In Fuest, C. and R, Z. G., editors, *Critical Issues in Taxation and Development*, pages 45–64. The MIT Press.

Gordon, R. and Li, W. (2009). Tax structures in developing countries: Many puzzles and a possible explanation. *Journal of Public Economics*, 93(7-8):855–866.

Gordon, R. H., Hines, J. R., and Summers, L. (1987). Notes on the Tax Treatment of Structures. In Summers, L., editor, *The Effects of Taxation on Capital Accumulation*, pages 223–257. University of Chicago Press, Chicago.

Graham, J. R., Hanlon, M., Shevlin, T., and Shroff, N. (2017). Tax rates and corporate decision-making. *Review of Financial Studies*, 30(9):3128–3175.

Granja, J., Makridis, C., Yannelis, C., and Zwick, E. (2020). Did the Paycheck Protection Program Hit the Target? *NBER Working Paper 27095*.

Gravelle, J. G. (1982). Effects of the 1981 Depreciation Revisions on the Taxation of Income from Business Capital. *National Tax Journal*, 35:1–20.

Gregory, V., Menzio, G., and Wiczer, D. (2020). Pandemic Recession: L- or V-Shaped? *NBER Working Paper 27105*.

Gronberg, S. (2015). Tekevätkö yritykset korotettuja poistoja? Technical report, VATT Institute for Economic Research, Helsinki.

Guceri, I. and Albinowski, M. (2021). Investment responses to tax policy under uncertainty. *Journal of Financial Economics*, pages 1–63.

Guenther, G. (2018). The Section 179 and Section 168(k) Expensing Allowances: Current Law and Economic Effects. *Congressional Research Service Report*.

Hall, R. E. and Jorgenson, D. W. (1967). Tax policy and investment behavior. *The American Economic Review*, 57(3):391–414.

Hassett, K. A. and Hubbard, G. R. (2002). Tax policy and business investment. *Handbook of Public Economics*, 3:1293–1343.

Heckman, J. J. (1979). Sample Selection Bias as a Specification Error. *Econometrica*, 47(1):153.

Hoseini, M. (2020). Value-Added Tax, Input–Output Linkages and Informality. *Economica*, 87(347):813–843.

Hoseini, M. and Briand, O. (2020). Production efficiency and self-enforcement in value-added tax: Evidence from state-level reform in India. *Journal of Development Economics*, 144(October 2018).

House, C. L. and Shapiro, M. D. (2008). Temporary Investment Tax Incentives: Theory with Evidence from Bonus Depreciation. *American Economic Review*, 98(3):737–768.

Huang, Y. and Luk, P. (2020). Measuring economic policy uncertainty in China. *China Economic Review*, 59(October 2019):101367.

Iacus, S. M., King, G., and Porro, G. (2011). Multivariate Matching Methods That Are Monotonic Imbalance Bounding. *Journal of the American Statistical Association*, 106(493):345–361.

IMF (2020). International Monetary Fund Policy Tracker.

International Labour Organization (2020). Social Protection Responses to COVID-19 Crises around the World.

Kanniainen, V. and Sodersten, J. (1994). Cost of monitoring and corporate taxation. *Journal of Public Economics*, 2727(94).

Kaplan, G., Moll, B., and Violante, G. L. (2020). The Great Lockdown and the Big Stimulus:Tracing the Pandemic Possibility Frontier for the U.S. *BFI Working Paper No, 2020-119*.

Kitchen, J. and Knittel, M. (2016). Business Use of Section 179 Expensing and Bonus Depreciation, 2002-2014. *Office of Tax Analysis Working Paper Series*, 110(October).

Li, J. and Wang, X. (2020). Does VAT have higher tax compliance than a turnover tax? Evidence from China. *International Tax and Public Finance*, 27(2):280–311.

Li, L., Liu, K. Z., Nie, Z., and Xi, T. (2021). Evading by any means? VAT enforcement and payroll tax evasion in China. *Journal of Economic Behavior and Organization*, 185:770–784.

Liu, L. and Lockwood, B. (2018). VAT Notches, Voluntary Registration, and Bunching: Theory and UK Evidence. *Working Paper*, (July).

Liu, L., Lockwood, B., Almunia, M., and Tam, E. H. F. (2019). VAT Notches, Voluntary Registration, and Bunching: Theory and UK Evidence. *Review of Economcis and Statistics*, Just Accep.

Liu, Y. and Mao, J. (2019). How do tax incentives affect investment and productivity? Firm- level evidence from China. *American Economic Journal: Economic Policy*, 11(3):261–291.

Loayza, N. and Pennings, S. (2020). Macroeconomic Policy in the Time of COVID-19: A Primer for Developing Countries. *World Bank Group Research and Policy Briefs*, 1(28).

Maffini, G., Xing, J., and Devereux, M. P. (2019). The Impact of Investment Incentives: Evidence from UK Corporation Tax Returns. *American Economic Journal: Economic Policy*, 11(3):361–389.

Maitra, P., Smyth, R., Nielsen, I., Nyland, C., and Zhu, C. (2007). Firm Compliance with Social Insurance Obligations Where There is a Weak Surveillance and Enforcement Mechanism: Empirical Evidence from Shanghai. *Pacific Economic Review*, 5(June):577–596.

Mao, J., Zhang, L., and Zhao, J. (2013). Social Security Taxation and Compliance: The Chinese Evidence. *SSRN Electronic Journal*.

McKenzie, D. and Seynabou Sakho, Y. (2010). Does it pay firms to register for taxes? The impact of formality on firm profitability. *Journal of Development Economics*, 91(1):15–24.

Ministry of Human Resources and Social Security (2019). 2019 Human Resources and Social Security Development Statistics Annual Report. Technical report.

Nielsen, I. and Smyth, R. (2008). Who bears the burden of employer compliance with social security contributions? Evidence from Chinese firm level data. *China Economic Review*, 19:230–244.

Nyland, C., Smyth, R., and Zhu, C. J. (2006). What Determine the Extent to which Employers will Comply with their Social Security Obligations? Evidence from Chinese Firm-level Data. *Social Policy and Adminsitration*, 40(2).

Nyland, C., Thomson, S. B., and Zhu, C. J. (2011). Employer attitudes towards social insurance compliance in Shanghai, China. *International Social Security Review*, 64.

OECD (2019). *Tax Administration 2019: Comparative Information on OECD and Other Advanced and Emerging Economies*. OECD Publishing, Paris.

Ohrn, E. (2018). The effect of corporate taxation on investment and financial policy: Evidence from the DPAD. *American Economic Journal: Economic Policy*, 10(2):272–301.

Ornelas, J. R. H., Pedraza, A., Ruiz-Ortega, C., and Silva, T. (2019). Winners and Losers When Private Banks Distribute Government Loans: Evidence from Earmarked Credit in Brazil. *World Bank Policy Research Working Paper*, (April).

Pham, A. (2019). Firm take-up of a corporate income tax cut: evidence from vietnam. *National Tax Journal*, 72(September):575–598.

Pomeranz, D. (2015). No taxation without information: Deterrence and self-enforcement in the value added tax. *American Economic Review*, 105(8):2539–2569.

Qiu, Q. and Wan, J. (2019). Depreciation Rate by Perpetual Inventory Method and Depreciation Expense as Accounting Item. `http://www.econ.fukuoka-u.ac.jp/researchcenter/workingpapers/WP-2019-012.pdf`.

Rickne, J. (2013). Labor market conditions and social insurance in China. *China Economic Review*, 27:52–68.

Schenk, A., Thuronyi, V., and Cui, W. (2015). *Value Added Tax: A Comparative Approach*. Cambridge University Press, New York, 2nd edition.

Smart, M. and Bird, R. M. (2009). The impact on investment of replacing a retail sales tax with a value-added tax: Evidence from Canadian experience. *National Tax Journal*, 62(4):591–609.

Song, Z., Storesletten, K., Wang, Y., and Zilibotti, F. (2015). Sharing High Growth across Generations: Pensions and Demographic Transition in China. *American Economic Journal: Macroeconomics*, 7(2):1–39.

Tang, J. and Feng, J. (2019). Collecting system of social insurance and contribution compliance–evidence from chinese firm-level data. *China Economic Quarterly*, 5.

Ulyssea, G. (2018). Firms, informality, and development: Theory and evidence from Brazil. *American Economic Review*, 108(8):2015–2047.

Ulyssea, G. (2020). Informality: Causes and consequences for development. *Annual Review of Economics*, 12:525–546.

Wales, T. J. (1966). Estimation of an Accelerated Depreciation Learning Function. *Journal of the American Statistical Association*, 61(316):995–1009.

Waseem, M. (2018). Taxes, informality and income shifting: Evidence from a recent Pakistani tax reform. *Journal of Public Economics*, 157(October 2016):41–77.

Yagan, D. (2015). Capital tax reform and the real economy: The effects of the 2003 dividend tax cut. *American Economic Review*, 105(12):3531–3563.

Zwick, E. (2021). The costs of corporate tax complexity. *American Economic Journal: Economic Policy*, 13(2):467–500.

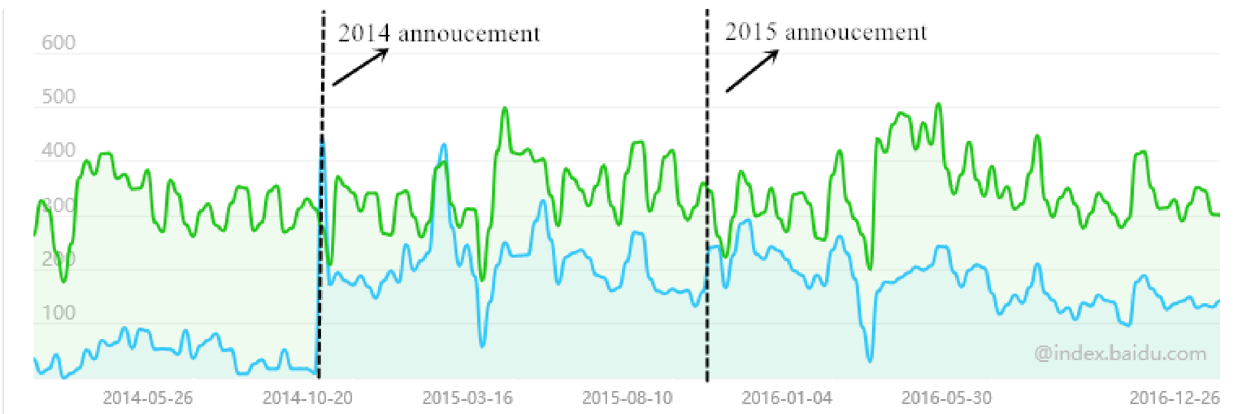
Zwick, E. and Mahon, J. (2017). Tax policy and heterogeneous investment behavior. *American Economic Review*, 107(1):217–248.

Appendix

A Chapter 1 Appendix

Search Intensity

Figure A.1: **Search Engine Queries for Accelerated Depreciation**



Note: This figure plots the intensity indices of search engine queries from the Chinese website Baidu during the period January, 2014-December, 2016. The shaded blue series is the index for the key words "fixed assets accelerated depreciation" and the green series is the index for the key words "tax reporting". Both key words are in Chinese. The dashed black lines indicate the weeks for the 2014 and 2015 AD policy announcements.

Matching and Regression Weights

Regression weights for the DiD analysis are constructed in two steps. First, we match on base year observables using Coarsened Exact Matching (CEM) [Iacus et al., 2011] as described in the main text and calculate weights following their recommended procedure. CEM first coarsens the matching variables by sorting values of each variable into mutually exclusive bins. It then creates *strata*, which are simply interactions of the bins. For example, with two matching variables, each grouped into two bins, CEM would create four strata from the product of each binned variable. Targeted and control firms are then exactly matched based on which of the four cells they belong in.[93]

[93] Before CEM matching, we restrict the treatment and control samples to have a common support for each of the matching variables and drop firm-year observations with zero business revenue.

The regression weights are constructed as follows. Denote N_c and N_d the total number of matched control and treated firms. For each strata s, we calculate the number of control firms N_c^s and the number of treated firms N_d^s. Treated firms are given a regression weight h_i of one. Control firms are assigned regression weights proportional to the number of control firms, relative to the number of treated firms, in the strata: $h_i = \frac{N_c}{N_d}\frac{N_d^s}{N_c^s}$. Table A.1 shows the descriptive statistics among the matched treatment and control groups.

Second, we use the re-weighting method of DiNardo et al. [1996] to flexibly control for changes in the firm distribution between control and treated industries, as in Yagan [2015] and Zwick and Mahon [2017]. The re-weighting procedure proceeds as follows. First, we create ten bins (b) corresponding to the deciles of the revenue distribution for the control firms in the year before the policy implementation (base year). The DFL weights ($w_{i,t,g,b}$) for firm i, with revenue in bin b, in group g (where a group is a treatment status-year pair) are:

$$w_{i,t,g,b} = h_i \times \frac{\sum_{i' \in b \,\cap\, i' \in \underline{g}} h_{i'}}{\sum_{i' \in b \,\cap\, i' \in g} h_{i'}} \times \frac{\sum_{i' \in g} h_{i'}}{\sum_{i' \in \underline{g}} h_{i'}} \tag{A.1}$$

where $\underline{g}$ is the control group in the base year. These weights capture changes in the distribution of firm size (revenue) over time. One may be concerned that this attenuates the treatment effect towards zero if investment growth caused by the AD policy is correlated with revenue growth. In our setting, results are highly similar without DFL re-weighting – using h_i rather than $w_{i,t,g,b}$.

Table A.1: **Matched Difference-in-Difference Sample**

Panel A: 2014 Change	Not Matched					Matched				
	Targeted		Control			Targeted		Control		
	Mean	N	Mean	N	*p*	Mean	N	Mean	N	*p*
Total Assets	5304	3334	6179	7114	0	7950	1014	9780	1497	0
Profit Margin	-.27	3146	-.08	6965	0	-.03	1014	-.04	1497	.4
Revenue Growth	.3	2730	.05	6424	0	.07	980	.05	1458	.4
Age	12.13	3334	16.12	7114	0	16.12	1014	15.91	1497	.28
Asset Growth Net of Depreication	.07	1616	.04	3530	.04	.07	1014	.04	1497	.16
Fixed Assets Net of Depreciation	443.14	3334	521.29	7114	.03	1041.72	1014	1309.34	1497	.01
Fixed Assets Historical Cost	1362.8	3334	1767.91	7114	0	1987.16	1014	2856.14	1497	0
Business Revenue	3346	3319	5228	7106	0	5241	1014	7551	1497	0
Taxable Income	178.62	3334	137.46	7113	0	327.46	1014	359.29	1497	.39
Tax Loss Stock	39	3334	51	7114	0	33	1014	57	1497	0
Percent In Tax Losses	.34	3334	.26	7114	0	.2	1014	.21	1497	.58
Average Useful Life	8.89	3334	11.41	7114	0	10.92	1014	11.44	1497	0
State or Collectively Owned	.04	3334	.1	7114	0	.04	1014	.06	1497	0
Small or Micro Enterprise (SME)	.57	3334	.57	7114	.82	.4	1014	.41	1497	.7
Distance to Bureau (km)	9.81	2364	13.13	5760	0	10.74	707	12.11	1115	0
Firms/Bureau Employees	274	2408	216	5762	0	348	825	321	1222	0
Panel B: 2015 Change	**Not Matched**					**Matched**				
	Targeted		Control			Targeted		Control		
	Mean	N	Mean	N	*p*	Mean	N	Mean	N	*p*
Total Assets	5096	15620	6013	7114	0	5993	5575	6590	3023	0
Profit Margin	-.04	15334	-.05	6965	0	-.03	5575	-.03	3023	.82
Revenue Growth	.05	14288	.03	6424	0	.04	5376	.03	2926	.22
Age	15.8	15620	16.14	7114	0	16.15	5575	16.13	3023	.84
Asset Growth Net of Depreication	.05	7943	.04	3530	.33	.05	5575	.04	3023	.27
Fixed Assets Net of Depreciation	467.14	15620	495.95	7114	.16	892.17	5575	894.59	3023	.95
Fixed Assets Historical Cost	1591.48	15620	1709.75	7114	.04	1823.92	5575	1896.19	3023	.46
Business Revenue	3893	15601	4928	7106	0	4611	5575	5588	3023	0
Taxable Income	96.31	15620	124.54	7113	0	140.9	5575	159.96	3023	.09
Tax Loss Stock	40	15620	49	7114	0	42	5575	51	3023	0
Percent In Tax Losses	.25	15620	.26	7114	.9	.23	5575	.23	3023	.47
Average Useful Life	11.56	15620	11.41	7114	0	11.41	5575	11.17	3023	0
State or Collectively Owned	.07	15620	.1	7114	0	.05	5575	.06	3023	0
Small or Micro Enterprise (SME)	.58	15620	.57	7114	.11	.52	5575	.51	3023	.46
Distance to Bureau (km)	12.71	12669	13.13	5760	0	13.09	4098	12.61	2260	.02
Firms/Bureau Employees	257	13116	216	5762	0	390	4514	330	2471	0

Note: This table reports descriptive statistics of key variables in 2013 for the unmatched and matched samples using non-targeted manufacturing firms as the control group. Dollar values are reported in 10,000 CNY. Firm-year observations with zero fixed assets are excluded. The matching process is described in Section 2.3. The first five columns report the mean, sample size, and p-value for the difference of means for the targeted and control firms without matching. The last five columns report the same using the set of matched firms. Profit margin is the ratio of total pre-tax profit over business revenue. The stock of tax losses are the unclaimed tax losses accumulated since 2010. Average useful life is the dollar-weighted average tax-life of firms' asset holdings. All continuous variables are winsorized at the 1st and 99th percentiles within each group.

Cost of Capital Regression

This section presents an alternative approach to calculating user cost elasticities that uses the policy reform as an instrument in the following specification:

$$y_{it} = \gamma_t + \gamma_i + \eta Ln(\frac{1 - \tau_{i,t} Z_{i,t}}{1 - \tau_{i,t}}) + \epsilon_{it} \tag{A.2}$$

where $Ln(\frac{1-\tau_{i,t}Z_{i,t}}{1-\tau_{i,t}})$ is the UCC (introduced in section 2.1) and η is the effect of the UCC on y. We instrument for the UCC using the policy change:

$$Ln(\frac{1 - \tau_{i,t} Z_{i,t}}{1 - \tau_{i,t}}) = \pi_t + \pi_i + \pi D_i \times Post_t + u_{it} \tag{A.3}$$

where the instrument is $D_i \times Post_t$. Table A.2 reports the estimate of η and the 95 percent confidence intervals. Note, this coefficient should be negative if investment increases when the tax component of the user cost of capital decreases. For both the 2014 and the 2015 treatments, the confidence intervals for the point estimates contain zero, which is consistent with the DiD results reported in Table 2.4 of the paper.

The estimates of η for $Ln(K_t)$ are elasticities of the capital stock with respect to the UCC — a 1% increase in the UCC causing a .59% and .4% decrease in the capital stock, for the 2014 and 2015 policy cohorts respectively.

The estimates of η for $Ln(K_t) - Ln(K_{t-1})$ are semi-elasticities of the UCC with respect to the investment rate (I_t/K_{t-1}) (recall, we argued in Section 2.3 that the treatment effect on $Ln(K_t) - Ln(K_{t-1})$ closely approximates the treatment effect on I_t/K_{t-1}). To convert the semi-elasticity to an elasticity, η must be divided by the average I_t/K_{t-1} (in the pre-period). As shown in Section 2.3, $\frac{I_t}{K_{t-1}} = \frac{K_t - K_{t-1}}{K_{t-1}} + \frac{(1-\gamma)S_t}{K_{t-1}} + \gamma$. We observe $\frac{K_t - K_{t-1}}{K_{t-1}}$ in our data: .069 and .0485 for the 2014 and 2015 groups, respectively, from in the pre-AD period (Table 2.4). We do not observe $\frac{(1-\gamma)S_t}{K_{t-1}} + \gamma$, and so rely on an estimate from Qiu and Wan [2019] of .0953 for the same years to construct estimates of the average pre-period I_t/K_{t-1} of .164 and .144 respectively. We divide these into the 90% bound of η reported in Table A.2 (-.41 and -1.14) to get bounds on the elasticity of 1.1 and 3.7 (absolute values, as in the main text).

Table A.2: **User Cost Regression**

Cost of Capital Elasticity Estimates (2SLS)

	$Ln(K_t) - Ln(K_{t-1})$		$Ln(K_t)$	
	2014	2015	2014	2015
Log User Cost	1.86	0.15	-0.59	-0.40
	[-0.41,4.12]	[-1.14,1.43]	[-4.34,3.16]	[-3.02,2.22]
N	9343	31880	12018	41091
Treated Firms	1014	5615	1046	5818
Untreated Firms	1499	3041	1566	3176

Note: This table presents estimates of equation (A.2). Standard errors are clustered at the three-digit industry level. 90% confidence intervals are shown in square brackets.

Specification and Outcome Robustness

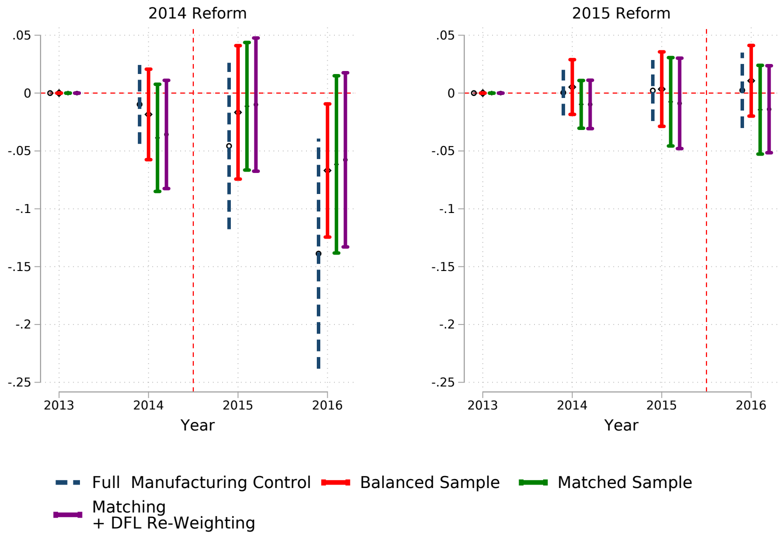
Table A.3: **Impact of AD on Investment–Robustness Checks**

	$\frac{K_{t,net}-K_{t-1,net}}{Sales_{2010-2013}}$		Historical Cost		Time × Ind		Excl. RD Claimers		Excl. SMPE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	2014	2015	2014	2015	2014	2015	2014	2015	2014	2015
Treat × Post	-0.57	0.27	-0.88	0.05	-1.48	1.07	-3.13	0.03	0.23	2.48
	(0.58)	(0.35)	(1.86)	(0.80)	(3.39)	(2.80)	(3.48)	(1.59)	(2.88)	(1.66)
N	10131	34646	13680	46588	10013	34304	3349	31052	5024	14962
Treated Firms	1059	5891	1036	5733	1055	5868	355	5352	611	2697
Untreated Firms	1592	3227	1556	3136	1583	3208	612	2875	804	1526
Treated Clusters	37	90	37	90	37	90	37	90	37	90
Untreated Clusters	44	44	44	44	44	44	44	44	44	44
Dep. Var. Mean	1.09	0.38	12.46	10.51	6.90	4.85	8.18	3.96	8.36	8.25

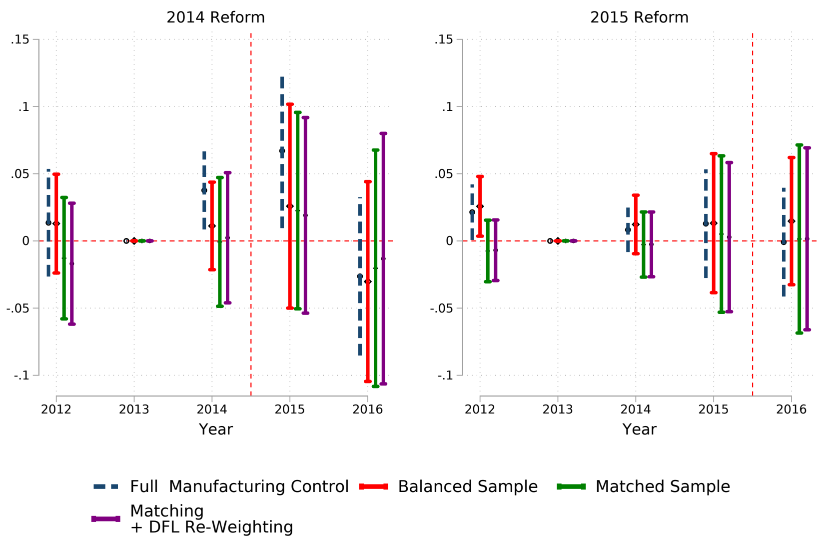
Note: This table reports robustness checks on the DiD estimation. The first two models use alternative outcomes: (i) the year-over-year change in the fixed asset stock measured net of accounting depreciation normalized by sales in the pre-policy period and (ii) $Ln(K_t) - Ln(K_{t-1})$ where K is measured at historical cost from the tax returns. The remaining columns use the baseline outcome: $Ln(K_t)-Ln(K_{t-1})$ where K is measured net of accounting depreciation. The third model includes linear time trends at the three digit industry level. The fourth model removes firms that ever claimed the RD super deduction. The fifth model excludes Small and Micro-profit Enterprises (SMPEs). Standard errors are robust clustered at the three digit industry level. Coefficients and Dep. Var. Mean are scaled by 100. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A.2: **Dynamic Difference-in-Difference**

a **Outcome:** $Ln(K_t) - Ln(K_{t-1})$



b **Outcome:** $Ln(K_t)$



Note: This figure plots the estimated dynamic DiD coefficients β_s and 95 percent confidence intervals from the following specification: $y_{i,t} = \alpha_t + \alpha_i + \sum_{s \neq 0} \beta_s \times 1\{t = s\} \times D_i + \epsilon_{i,t,k}$ where time t is normalize to zer0 in 2013. The Manufacturing Control series restricts the control group to manufacturing industries. The final three series (a) restrict to firms present for all seven years, (b) restrict the matched sample as described in Section 2.3, and (c) restrict to matched sample and DFL re-weight. Our baseline results presented in the main text correspond to specification (c). Standard errors are clustered at the three digit industry level. Panels A and B presents results for the outcomes $Ln(K_t) - Ln(K_{t-1})$ and $Ln(K_t)$ respectively. Outcomes are winsorized at the 1 and 99% level in each year and treated/control group.

A Combined Dynamic DiD Specification

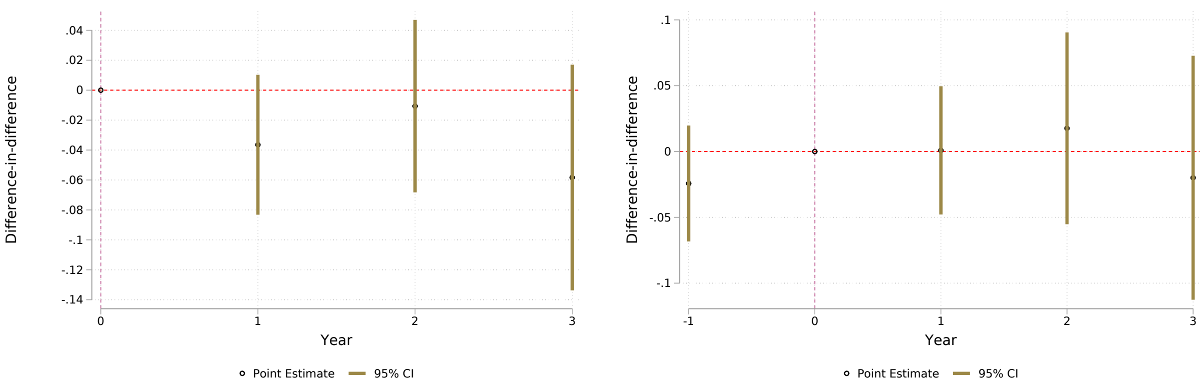
We center time around policy implementation and then pool the two treatment groups together to run a single dynamic difference in difference. The pooled specification is as follows:

$$Y_{it} = \alpha_t + \alpha_i + \gamma D_i + \sum_{s \neq 0} \beta_s \mathbb{1}_s \times D_i + \epsilon_{it} \tag{A.4}$$

Where as before, α_t and α_i are year and firm fixed effects. D_i denotes being in a targeted industry. We define event time s as time centered around policy implementation. So $s = 0$ corresponds to 2013 for the 2014 targeted industries and 2014 for the 2015 industries. Figure A.3 shows the results.

Figure A.3: **Pooled Event Study**

a **Outcome:** $Ln(K_t) - Ln(K_{t-1})$ b **Outcome:** $Ln(K_t)$

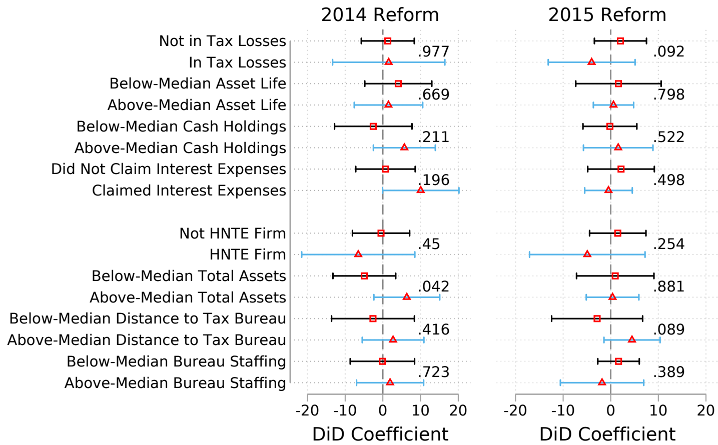


Note: This figure present estimates of β_s from equation (A.4) and 95% confidence intervals, using the baseline sample described in Section 2.3.

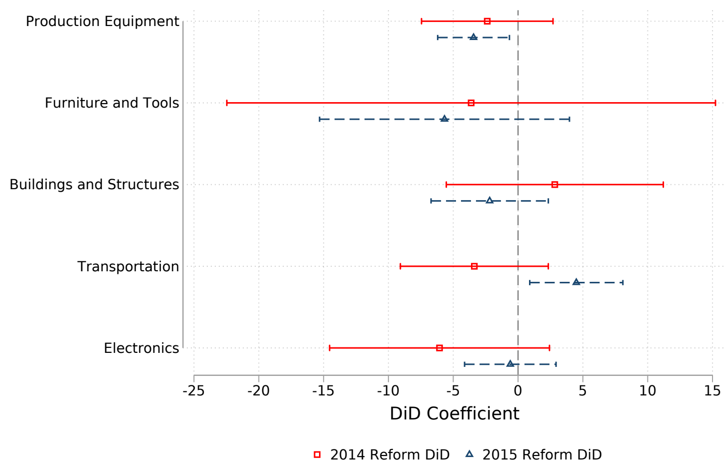
Additional Heterogeneity Results

Figure A.4: **Heterogeneous Responses to the Reform? (Using Outcome $Ln(K_t)$)**

a **By Firm Characteristics**



b **By Asset Type**



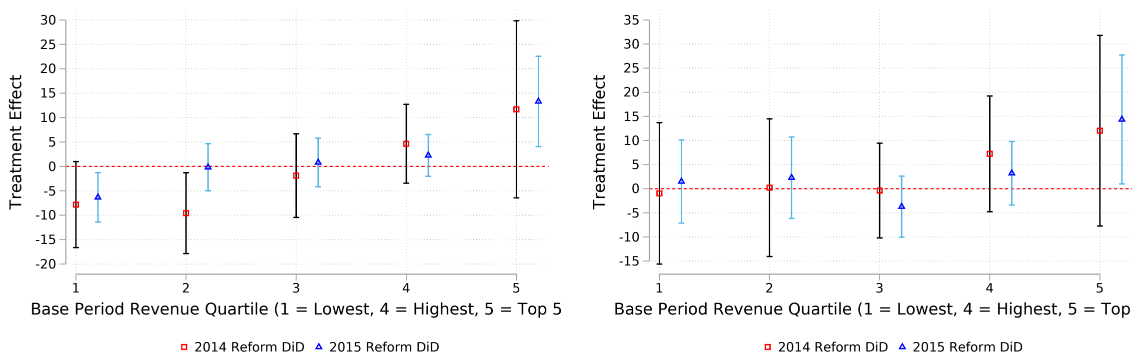
Note: Panel A plots estimates of β and 95% confidence intervals from equation (5.2) for subsets of the sample. For each of eight different firm characteristics X, we split the sample into above and below median when X is continuous, or by $X = 0$ and $X = 1$ when X is binary. The first four characteristics proxy for a firm's readiness to invest, and the how beneficial AD is for the firm. The last four characteristics proxy for a firm's informational awareness and sophistication. P-values for the test of the treatment effects being different are displayed to the right of the confidence intervals. Panel B plots estimates of β for the full sample of firms but estimated separately for asset class. The outcome is $Ln(K_t)$. In panel A, K is the firm's fixed asset stock measured at net of accounting depreciation from financial returns. In Panel B, since net-of-depreciation measures are not observed at the asset level, K is measured at original cost from tax depreciation returns. Estimates are scaled by 100 to be consistent with the estimates reported in Table 2.4.

Size Heterogeneity and Very Large Firms

Figure A.5 reproduces the size heterogeneity estimates from Figure 2.3, except using revenue rather than total assets to measure firm size. The results are very similar. Next, this section discusses the estimated treatment effect of the largest 5% firms, based on firms' pre-treatment revenue. The table at the bottom of Figure 2.3 shows that the largest 5% firms in the 2014 treated and matched control groups include 128 firms, and the largest 5% firms in the 2015 treated and matched control groups include 444 firms. The revenues for the smallest firms in these groups are CNY 270 million and CNY 233 million for the 2014 and 2015 treated firms, respectively. As a reference point, a manufacturing firm is officially classified as "large" in China if it has more than CNY 400 million in revenue and as "medium" if revenue lies between CNY 200 million and 400 million.

Figure A.5: **Responsiveness by Pre-Reform Revenue Quartiles**

a **Outcome:** $Ln(K_t) - Ln(K_{t-1})$ b **Outcome:** $Ln(K_t)$



Quartile	Left Endpoints		Number of Firms	
	2014	2015	2014	2015
1	0.04	0.08	664	2295
2	4.88	4.73	672	2299
3	13.22	11.60	656	2252
4	39.81	33.90	651	2230
5	270.39	232.25	128	443

Note: Panels A and B split firms into four quartiles based on pre-treatment average revenue (1 = smallest, 4 = largest). Each then plots estimates of β from equation 5.2 and 95% confidence intervals for each quartile. The fifth bin (5) plots β for the largest 5% of firms. Estimates are scaled by 100 to be consistent with the estimates reported in Table 2.4. K_t is fixed assets net of accounting depreciation. The table lists the quartile's left-endpoints, in 1,000,000CNY, and the number of firms in each.

In Figure A.6, we report estimation results for the dynamic response to AD, while controlling for firm and year fixed effects. For the 2015 AD policy, targeted firms in the top 5% show increased $Ln(K_t) - Ln(K_{t-1})$ in 2015, relative to control firms in the top 5% (Panel B). For both 2014 and 2015 cohorts, a larger divergence between the targeted and control large firms appears in 2016. The pattern is qualitatively similar when the outcome variable is $Ln(K_t)$ (Panels C and D). Figure A.6 also validates the parallel trend assumption. If we expand the regression sample to the largest 10% of firms, however, the positive investment response of the treated firms becomes smaller and loses statistical significance.

It thus appears that the largest 5% of firms in our sample of treated firms may have increased investment post AD. Figure A.7 shows that these firms also have higher rates of claiming AD benefits than the full sample. However, several considerations caution against interpreting the results as purely causal. For instance, the greatest response of the 2015 targeted large firms is observed in 2015, even though AD for the 2015 treated industries was announced in September 2015. Such a quick response may not seem plausible (given adjustment costs, the speed of decision-making at large firms, etc.), and also stands in contrast with the delayed response of the 2014 treated firms. Moreover, the declining investment observed in the top 5% control firms during 2015-2016 may also be driving the positive treatment effect of top 5% treated firms.

Figure A.6: **Growth of Fixed Assets Net of Depreciation**

a **2014 Policy Change:** $Ln(K_t) - Ln(K_{t-1})$

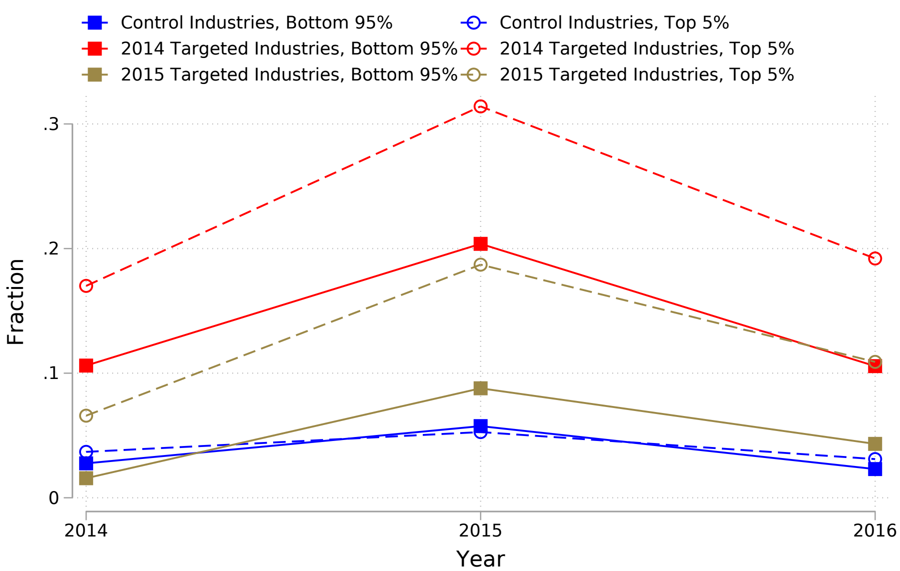
b **2015 Policy Change:** $Ln(K_t) - Ln(K_{t-1})$

c **2014 Policy Change:** $Ln(K_t)$

d **2015 Policy Change:** $Ln(K_t)$

Note: This figure restricts the sample to firms in the top 5% of the revenue distribution as of 2013. Panels A and B plot trends in $Ln(Kt) - Ln(K_{t-1})$ while Panels C and D plot trends in $Ln(K_t)$. In all four, K is fixed assets net of accounting depreciation as reported on balance sheets. Trends are plotted separately for the matched treated and control firms. The control firms are those in non-targeted manufacturing industries and matched as described in Section 2.3. For each panel, we estimate a dynamic version of equation (5.2) as $y_{i,t} = \alpha_t + \alpha_i + \sum_{s \neq 2013} \beta_s \times \mathbb{1}\{t = s\} \times D_i + \epsilon_{i,t,g}$. We then plot α_t for the control group and $\alpha_t + \beta_t$ for the treatment group and the associated 95% confidence intervals. The vertical red lines indicate the timing of the AD policy announcement and implementation.

Figure A.7: **Comparing Full Sample Claiming Rates to Largest 5% Claiming Rates**



Note: This figure plots the fraction of firms, in each year, with positive AD deductions reported on their tax return, among the set of firms that had at least one year-over-year increase in fixed assets net of depreciation during the AD years. The sample is split into non-targeted industries, 2014 targeted industries, and 2015 targeted industries. Firms in these industries are then further separated into either the top 5% or bottom 95% of the firm revenue distribution.

Results from Orbis Data

Figure A.8: **Growth of Fixed Assets Net of Depreciation from Orbis**

Note: This figure plots trends in $Ln(K_t) - Ln(K_{t-1})$, where K is fixed assets net of accounting depreciation, from Orbis. For each panel, we estimate a dynamic version of equation (5.2) as $y_{i,t} = \alpha_t + \alpha_i + \sum_{s \neq 2013} \beta_s \times \mathbb{1}\{t = s\} \times D_i + \epsilon_{i,t,g}$. We then plot α_t for the control group and $\alpha_t + \beta_t$ for the treatment group and the associated 95% confidence intervals. The vertical red lines indicate the timing of the AD policy announcement and implementation.

Comparison to Fan and Liu [2020]'s Analysis of 2014 Reform

The empirical setup in Fan and Liu [2020] differs from ours in the following ways:

1. **Data:** They use the National Taxpayer Survey Data (NTSD). Our data come from administrative tax records and financial statements for a single province. This results in differences in sample composition, policy group studied, time period covered, and outcome measures.

2. **Sample Composition:** Theirs is a national sample of mostly large and medium firms, corresponding roughly to the top size quartile of our provincial sample.

3. **Reform Studied:** Their NTSD sample ends in 2015. They therefore study only the 2014 treatment and only have one post-period. We study both the 2014 and 2015 treatments and have two post periods for the former. The treatment group in the 2014 treatment is approximately 1/5th the size of the broader 2015 treatment group in our data and in the nationwide Orbis data.

4. **Outcome Measure:** The NTSD contains reports of investment expenditure. Chinese corporate tax returns do not require taxpayers to report investment expenditures and therefore our data does not contain this measure. We instead measure changes in asset stock recorded on balance sheets and tax returns. Their outcome measure is $Ln(I_t)$ and therefore they drop all observations with $I_t = 0$.[94]

[94] This generates potentially severe censoring.

5. **Control Group:** They use all non-targeted firms as the control group. This includes non-manufacturing industries. We instead use only non-targeted manufacturing firms, which are much more similar to the treated industries.

6. **Specification:** In their DiD analyses, in addition to including firm fixed effects, they interact year dummies with pre-treatment "average firm income, profit margin, and cash over asset share" in industry bins. We use firm fixed effects and match on pre-treatment covariates.

We address each of these differences below.

Sample composition: The NTSD sample is dominated by large and medium firms. Fan and Liu [2020] appear to report average sales of CNY 200 million, which would correspond to the top quartile of our sample. In addition, they report that larger firms in their sample of already-large firms responded more strongly to AD. In our heterogeneity analysis of investment responsiveness in Section 3.3 and Appendix A, we show that treated firms in the top quartile of our sample showed responsiveness by one measure of investment ($Ln(K_t)$), and the top 5% showed responsiveness by both $Ln(K_t)$ and $Ln(K_t) - Ln(K_{t-1})$. The different size composition of our samples, therefore, may be important to explaining the differences in our results.

Policy Studied and Timing: They study the 2014 treatment using a single post-treatment year (2015), whereas we use both 2015 and 2016 as the post-period. Panel A and C in Figure 2.1 show that using just 2015 as the post-period leads to a larger treatment estimate among the full sample; in the treatment group both $Ln(K_t) - Ln(K_{t-1})$ and $Ln(K_t)$ increase in 2015 relative to the control group, but then converge back towards the control group in 2016. Panel A of Figure A.8 likewise shows a similar pattern using the Orbis nationwide data. This pattern would cause our treatment effects to look smaller than Fan and Liu [2020].

Difference in Outcome: Because they report estimates using investment expenditure, $Ln(I_t)$, the treatment effects are interpreted as percent changes in investment. To provide an approximate comparison to our estimates, assume that firms were in a steady state before the treatment, such that $I_{t-1} = I$ and $K_{t-1} = K$, and that S is zero. Starting from the steady state, what happens if investment increases by $X\%$? Setting $K_{t-1} = K$ and $I_t = I \times (1 + X/100)$ in equation (5.3) (from the asset accumulation model in Section 2.3) and re-arranging:

$$\frac{K_t}{K} - 1 = \frac{I}{K} \times (1 + X/100) - \gamma \tag{A.5}$$

For a given percent change in the investment level, the growth of the asset stock $\frac{K_t}{K} - 1$ depends on steady state (pre-treatment) level of $\frac{I}{K}$. Substituting K and I into equation (5.3) and re-arranging, one can show that $\frac{I}{K} = \gamma$ assuming $S = 0$. Therefore:

$$\frac{K_t}{K} - 1 = \gamma \times X/100 \tag{A.6}$$

Fan and Liu [2020] estimate that X was approximately 10 for the 2014 treatment industries in the first year after AD's implementation. If the rate of accounting depreciation is 10%, then a 10% increase in I_t relative to pre-treatment I increases K_t by approximately 1% relative to pre-treatment K. This is within the confidence intervals reported in Table 2.4.

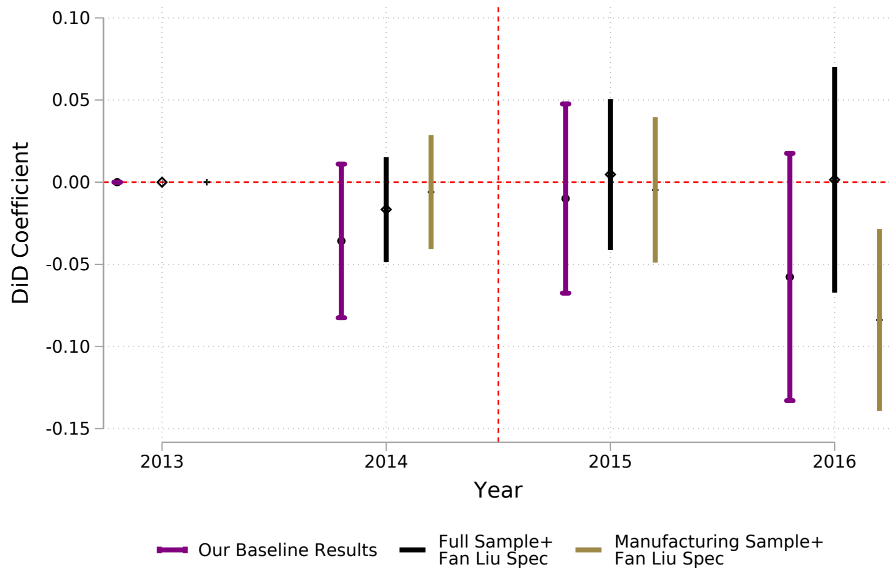
Difference in Empirical Approach: For comparison purposes, we present results using our data but with their specification and control group. Figure A.9 plots the estimated dynamic DiD coefficients β_s and 95 percent confidence intervals from the following specification:

$$y = \alpha_t + \alpha_i + \sum_{s \neq 2013} \beta_s \times 1\{t = s\} \times D_i + \gamma X_i \sum_{s \neq 2013} \times 1\{t = s\} + \epsilon_{i,t,k} \tag{A.7}$$

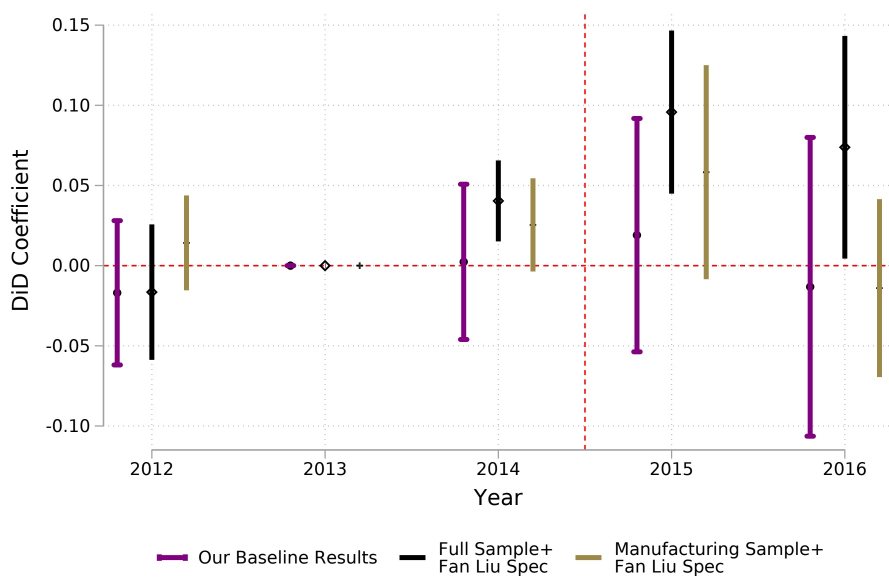
where α_t and α_i are fixed effects for year and firm respectively. X_i represents bins of the industry-level average pre-treatment taxable income, profit margin (business profits over business revenues), and cash over fixed assets. The Full Sample series uses all non-targeted firms in the control group including service industries. This is closest to Fan and Liu [2020]'s setup. The Manufacturing Control series restricts the control group to manufacturing industries. The third series shows our baseline result described in the paper for comparison, which excludes $\gamma X_i \sum_{s \neq 2013} \times 1\{t = s\}$ but matches firms on similar pre-treatment covariates. When using $Ln(K_t) - Ln(K_{t-1})$ as the outcome, all three approaches deliver similar results, as shown in Panel A. Panel B shows that the full-sample Fan and Liu approach produces a positive treatment effect on $Ln(K_t)$, but with a substantial increase starting in 2014, which is difficult to interpret as causal since the AD policy was not announced until fall 2014. Using the Manufacturing sample and their specification, there is positive treatment effect in 2015, consistent with their results, but the treatment effect dissipates by 2016. Fan and Liu [2020]'s estimates would only capture the 2015 spike.

Figure A.9: **Comparison to Fan and Liu [2020] Approach**

a **Outcome:** $Ln(K_t) - Ln(K_{t-1})$



b **Outcome:** $Ln(K_t)$



Note: This figure plots dynamic DiD estimates of β_s from equation A.7 and 95% confidence intervals. See text above for details.

Additional Take-Up Results

Table A.4: **Claiming Rate of AD by Industry**

	Claim Rate
Agricultural and sideline food processing industry	0.101
Food manufacturing	0.110
Textile industry	0.113
Textile and apparel, apparel industry	0.132
Leather, fur, feathers and their products and footwear	0.134
Wood processing and wood, bamboo, rattan, palm, grass products industry	0.063
Furniture manufacturing	0.159
Paper and paper products industry	0.118
Printing and recording media reproduction industry	0.094
Culture, education, beauty, sports and entertainment products manufacturing	0.116
Chemical raw materials and chemical manufacturing	0.160
Pharmaceutical manufacturing	0.212
Chemical fiber manufacturing	0.120
Rubber and plastic products industry	0.135
Metal products industry	0.120
General equipment manufacturing	0.120
Special equipment manufacturing	0.278
Automotive Manufacturing	0.136
Railway, marine, aerospace and other transportation equipment manufacturing	0.201
Electrical machinery and equipment manufacturing	0.152
Computer, communications and other electronic equipment manufacturing	0.275
Instrumentation manufacturing	0.300
Telecommunications, radio and television and satellite transmission services	0.164
Internet and related services	0.101
Software and information technology services	0.105
Total	0.140

Note: This table plots the percent of firms within each industry that claimed accelerated depreciation at least once between 2014 and 2016.

Table A.5: **Present Value of Claimed and Unclaimed Tax Savings (1000s CNY)**

Treatment Group	Not Claimed			Claimed		
	Mean	Median	Total	Mean	Median	Total
2014 Treatment Group	24.88	1.67	176371	27.21	2.12	26937
2015 Treatment Group	21.97	1.64	543734	31.18	2.05	48117

Note: Table A.5 shows estimated tax savings from accelerated depreciation (AD) for investment, separately according to whether AD was actually claimed for the investment. All values are expressed in 1,000 CNY. Investment is defined as the year-over-year change in the value of assets in asset class k ($K_{k,t} - K_{k,t-1}$). A firm is deemed to have claimed AD on the investment if the year-over-year change in AD is positive: $AD_{k,t} > AD_{k,t-1}$. Tax savings are calculated as $\tau_{i,t} \times (NPV_{k,AD} - NPV_{k,Regular})$, where $\tau_{i,t}$ is the tax rate the firm faces in year t, and the last two terms are the net present value of depreciation deductions under AD and regular depreciation, respectively, for asset class k. This calculation assumes (1) that firms keep the asset for the entire length of its useful tax life, (2) that firms are in taxable positions during the entire duration of the asset's life, (3) that the firm's tax rate does not change, and (4) if a firm did not claim AD on positive investment in year t, we assume it would not claim in later years. We restrict to firms in a taxable position in the year of investment. The base tax rate $\tau_{i,t}$ is calculated as firm i's income tax liability over its observed taxable income in the year of investment (t). This is 25% unless the firm is eligible for statutory reductions for SMPE firms ($\tau_{i,t}$ = 10% or 20%) and HNTE firms ($\tau_{i,t}$ = 15%). Immediate expensing is assumed for imputed investment of value less than 5,000 CNY such that $NPV_{k,AD} = K_{k,t} - K_{k,t-1}$. The mean and median are calculated at the firm level after summing tax savings across asset types for each firm. The total sums the tax savings across all firm-asset class-year observations. Only observations in the treated years are included; 2014 to 2016 and 2015 to 2016 for the 2014 and 2015 treatment groups, respectively. Tax savings values are winsorized at the 1st and 99th percentiles for each treatment group before calculating the means, medians, and total amounts.

Table A.6: **Correlations between Tax Administration Variables and Tax Compliance Proxies**

	(1) Log(Firms / Bureau Staff)	(2) Log(Distance to Bureau)
Statutory Rate minus Cash ETR	-0.066	-0.049
	(0.047)	(0.044)
Fixed Assets / Revenue	-0.009	0.002
	(0.038)	(0.035)
Business Profits / Revenue	-0.229**	0.285***
	(0.095)	(0.094)
N	15146	14637
Three-Digit Industry FE	Yes	Yes
Prefecture FE	Yes	Yes
Mean STR - ETR	0.01	0.01
Mean (Fixed Assets / Revenue)	0.43	0.42
Mean (Business Profits / Revenue)	-0.02	-0.02

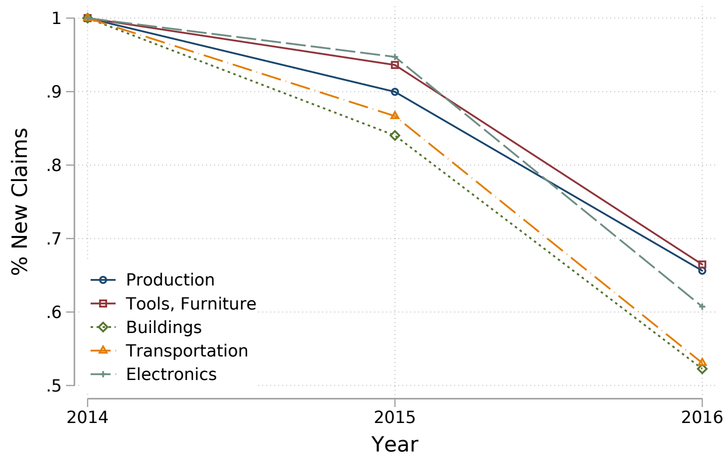
Note: This table provides additional results related to the concern that the distance between the firm and the tax office, and the ratio of firms to tax bureau staff, may be correlated with firms' tax non-compliance. We examine the correlation between the tax administration variables and three proxies for firms' non-compliance tendency. Our conjecture is that firms whose effective tax rates (ETRs) are much lower than the statutory rates may be less compliant; firms with more tangible fixed assets may be more compliant since it is easier for the tax bureau to verify their assets; and firms with a higher ratio of profits to revenue should be more compliant. We do not find the gap between ETR and statutory rate, or the ratio of fixed assets to total assets, is significantly associated with our two tax administration variables. While we find that firms located in areas where the ratio of firms to tax bureau staffs is higher report lower profit/revenue, those located further away from the tax bureau report higher profit/revenue. Overall, we do not find systematic evidence that firms located further away from tax offices, or firms facing a higher ratio of firms to tax bureau staffs, are more likely to avoid tax.

Table A.7: **Predictors of Claiming: Accounting Resources**

	Pr(Claim | Invest)			
	(1)	(2)	(3)	(4)
Log(# Accountants / # Workers)	-0.42			0.18
	(0.44)			(0.51)
Ln(# Accountants / # Firms)		-0.68***		-0.69**
		(0.25)		(0.29)
Ln(# Accounting Firms / # Firms)			-0.01	-0.32
			(0.42)	(0.44)
Ln(# Firms / # Tax Administrators)	-1.65***	-1.97***	-1.89***	-2.00***
	(0.35)	(0.34)	(0.35)	(0.38)
Log(Distance to Tax Bureau)	-0.63**	-0.83***	-0.76***	-0.83***
	(0.30)	(0.32)	(0.26)	(0.32)
Firm Characteristics	Yes	Yes	Yes	Yes
Two-Digit Industry FE	Yes	Yes	Yes	Yes
Prefecture FE	Yes	Yes	Yes	Yes
N	24555	24555	34374	24555
Claim Rate	6.30	6.30	6.85	6.30

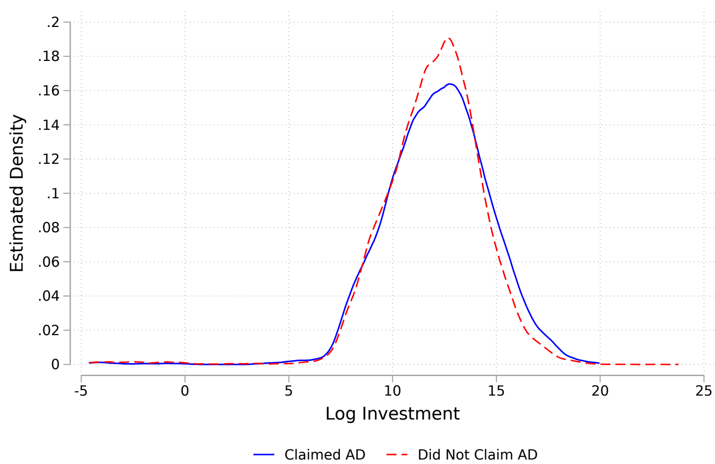
Note: This table reports the estimated average marginal effects of regional accounting resources on the probability of claiming AD conditional on having purchased eligible investment using the probit model described in Section 2.5. Claiming and investment are defined as in Table 2.5. The measures of accounting resources are described in Section 2.5.3. Coefficients are scaled by 100. All continuous covariates are winsorized at the 1st and 99th percentiles within each year for each of the two treatment groups. Standard errors are computed using the delta-method and are clustered at the three-digit industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A.10: **New AD Claims as % of Total Claims**



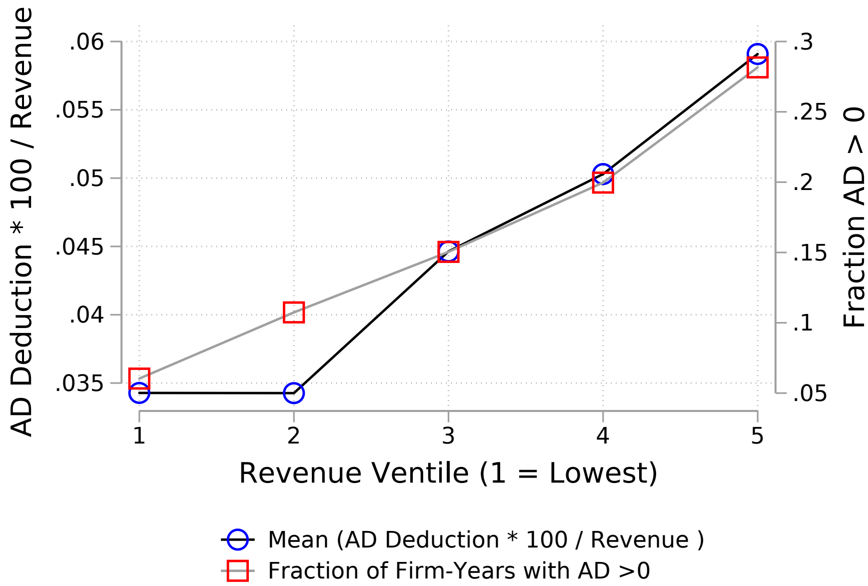
Note: This figure plots the percentage of first-time AD claims in total claims by asset type during the period 2014-2016.

Figure A.11: **Distribution of Investment by Claimed Status**



Note: This figure plots the distribution of investment (in logs) separately by whether AD was claimed on that investment. Investment is defined as the year-over-year change in the value of assets in asset class k ($K_{k,t} - K_{k,t-1}$). Observations with $K_{k,t} - K_{k,t-1} \leq 0$ are excluded. A firm is deemed to have claimed AD on the investment if $AD_{k,t} > AD_{k,t-1}$. The density is estimated using the Epanechnikov kernel and a bandwidth of .23 and .43 for the unclaimed and claimed distributions respectively.

Figure A.12: **Tax Savings Across the Firm Size Distribution**

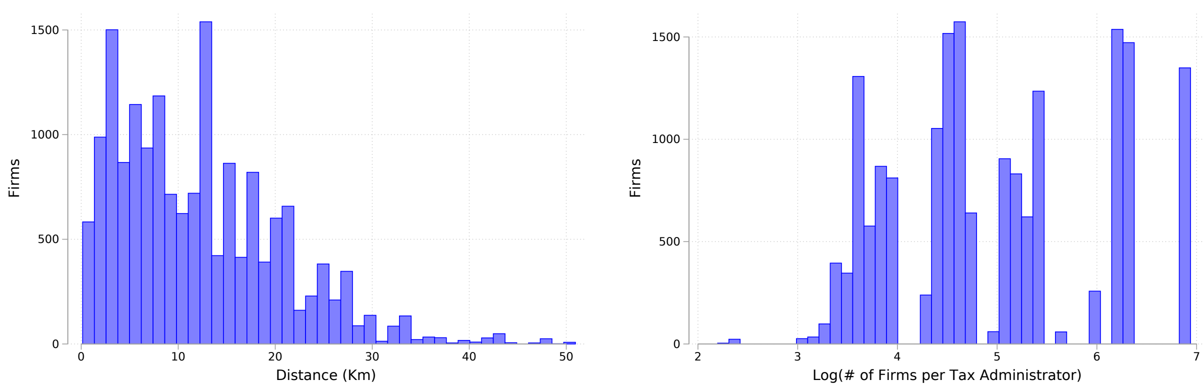


Note: This figure plots $\frac{1}{N}\sum_{i,t} AD_{i,t} \times 100/\text{Revenue}_{i,t}$ in each firm revenue ventile, to illustrate the size-gradient of AD tax deductions.

Figure A.13: **Distributions of Tax Bureau Characteristics**

a **Distance to Tax Bureaus**

b **Firms Per Tax Administrator**



Note: These figures plot the distributions in 2013 of firms' distance to their local tax bureau and the number of firms the bureau oversees divided by the bureau's number of employees. Only firms in the targeted industries are kept.

Selection Model

This section provides further details for the selection model specification used in Section 2.4. In this model, a firm in time t chooses to invest in assets of type k if their latent payoff function ($U_{i,k,t}$) is positive. The firm claims AD on that investment if the net benefit of doing so ($NB_{i,t,k}$) is positive. Both $U_{i,k,t}$ and $NB_{i,t,k}$ are functions of observables $X_{i,t}$:

$$I_{i,k,t} = 1 \text{ if } U_{i,k,t} = \beta X_{i,t} + \eta_{i,k,t} > 0 \tag{A.8}$$

$$C_{i,k,t} = 1 \text{ if } I_{i,k,t} = 1 \text{ and } NB_{i,t,k} = \gamma X_{i,t} + \epsilon_{i,k,t} > 0 \tag{A.9}$$

We are interested in how covariates $X_{i,t}$ predict the likelihood of claiming AD conditional on having eligible investment: $\frac{\partial P(C_{i,k,t}=1|I_{i,k,t}=1)}{\partial X_{i,t}}$. If we simply restrict to firms with investment ($I_{i,k,t} = 1$) and correlate take-up decisions with $X_{i,t}$, selection bias arises if the idiosyncratic errors $\epsilon_{i,k,t}$ and $\eta_{i,k,t}$ are correlated [Heckman, 1979]. As an example, assume that firm size increases the latent payoff of investing, and that the error terms are positively correlated. In this case, only small firms with idiosyncratically higher investment payoffs will invest. Due to the positive error correlation, these firms will also be more likely to claim, making small firms appear more likely to claim as well.

To account for this, we model the distribution of the error terms and their correlation. Error terms $\epsilon_{i,k,t}$ and $\eta_{i,k,t}$ are assumed to be jointly normally distributed allowing for non-zero co-variance. We then estimate β and γ by maximum likelihood. The resulting log likelihood contribution for firm i, in year t, in asset-class k can be written as

$$\begin{aligned} ln(L_{i,k,t}) &= (1 - I_{i,k,t})ln[P(I_{i,k,t} = 1)] + I_{i,k,t}(1 - C_{i,k,t})ln[P(I_{i,k,t} = 1, C_{i,k,t} = 0)] \\ &\quad + I_{i,k,t} \times C_{i,k,t} \times ln[P(I_{i,k,t} = 1, C_{i,k,t} = 1)] \\ &= (1 - I_{i,k,t})ln[\Phi(-X_{i,t}\beta)] + I_{i,k,t}(1 - C_{i,k,t})ln[\Phi(X_{i,t}\beta) \\ &\quad - \Phi(X_{i,t}\beta, X_{i,t}\gamma, \Omega)] + I_{i,k,t} \times C_{i,k,t} ln[\Phi(X_{i,t}\beta, X_{i,t}\gamma, \Omega)] \end{aligned}$$

where $I_{i,k,t}$ and $C_{i,k,t}$ are indicators for investing and claiming as defined in Section 5.1.2, Ω is the covariance matrix of $\epsilon_{i,k,t}$ and $\eta_{i,k,t}$ as in Equations (4) and (5), and Φ the cumulative distribution function for the normal distribution.

Omitting subscripts for simplicity, $Pr(C = 1 \mid I = 1)$ can be written as follows:

$$\begin{aligned} Pr(C = 1 \mid I = 1) &= P(X\delta + \eta_2 > 0 \mid X\beta + \eta_1 > 0) \\ &= \int_{-X\beta}^{\infty} \Phi((X\delta + \eta_1\Omega_{1,2}/\Omega_{2,2})/\sigma_{2|1})\phi(\eta_1; \sigma_1)d\eta_1 \left[\frac{1}{\Phi(X\beta/\sigma_1)}\right] \end{aligned}$$

And differentiating with respect to X, we have:

$$\frac{dPr(C \mid I)}{dX} = \big[\Phi((X\delta - X\beta\Omega_{1,2}/\Omega_{2,2})/\sigma_{2|1})\phi(-X\beta;\sigma_1)(\frac{dX\beta}{dX})+$$

$$\int_{-X\beta}^{\infty}\frac{d\Phi((X\delta - X\beta\Omega_{1,2}/\Omega_{2,2})/\sigma_{2|1})}{dX}\phi(\eta_1)d\eta_1\big]\,[\frac{1}{\Phi(X\beta/\sigma_1)}]-$$

$$[\int_{-X\beta}^{\infty}\Phi((X\delta+\eta_1\Omega_{1,2}/\Omega_{2,2})/\sigma_{2|1})\phi(\eta_1;\sigma_1)d\eta_1\big]\,[\frac{\phi(X\beta/\sigma_1)(\beta/\sigma_1)}{\Phi(X\beta/\sigma_1)^2}]$$

To aid in the identification, we include three variables in the investment ($U_{i,k,t}$) equation which are excluded from the claiming equation: the firm's lagged cash holdings, an indicator for whether a firm claimed interest expenses on their prior year's tax form, and the lagged growth rate of their fixed asset stock. Lagged cash holdings and interest expenses proxy for the ability to finance investments in year t, but should not affect the payoff of claiming AD. We include the firm's prior year measure of $Ln(K_t) - Ln(K_{t-1})$ as investment has been shown to have some degree of serial correlation [Cooper and Knittel, 2006].[95] In column (1) of Table A.8, we report the estimated marginal effects on the probability of investment in the current year. The dummy variable indicating interest expense deductions, firms' lagged cash holdings, and the firm's prior year's $Ln(K_t) - Ln(K_{t-1})$ all positively predict current investment and are jointly significant at the 1 percent level, partially validating them as effective excluded variables. The last two columns of Table A.8 show the average marginal effects of each predictor on the probability of claiming conditional on investing. As described in the main text, results are nearly identical to a simple probit model.

[95] The lagged measure of $Ln(K_t) - Ln(K_{t-1})$ would violate the exclusion restriction if we defined claiming as $AD(t) > 0$, as prior year's investments can entail AD claiming into the present. Defining claiming as $AD(t) > AD(t+1)$ controls for the concern.

Table A.8: **Predictors of Claiming: Firm-Level Characteristics**

	Selection Model		
	(1)	(2)	(3)
	Pr(Invest)	Pr(Claim | Invest)	
In Tax Loss Before AD	-7.11***	-2.69***	-2.73***
	(0.32)	(0.45)	(0.43)
Ln(Tax Loss Stock $_{t-1}$)	-0.20***	-0.09***	-0.08**
	(0.03)	(0.03)	(0.03)
Ln(Total Assets $_{t-1}$)	4.21***	0.39***	0.42***
	(0.21)	(0.15)	(0.14)
High and New Technology Enterprise	7.04***	2.27***	1.83***
	(0.62)	(0.61)	(0.59)
$Ln(K_{t,k} - K_{t-1,k})$		0.12***	0.09**
		(0.04)	(0.04)
Interest Deduction $_{t-1} > 0$	2.41***		
	(0.34)		
$Ln(K_{t-1}) - Ln(K_{t-2})$	3.78***		
	(0.38)		
Ln(Cash Holdings$_{t-1}$)	1.04***		
	(0.11)		
Two-Digit Industry FE	Yes	Yes	Yes
Prefecture FE	Yes	No	Yes
N	171846	171846	171846
Mean of Outcome Var.	28.32	6.36	6.36
Excluded Variables Joint P-value	0.000	0.000	0.000

Note: Column (1) reports the estimated average marginal effects of firm-level characteristics on $Pr(I_{i,t,k} = 1)$. Columns (2) and (3) report the estimated average marginal effects of firm-level characteristics on the probability of claiming AD conditional on having purchased eligible investment ($P(C_{i,t,k} = 1|I_{i,t,k} = 1)$). Claiming and investment are defined as outlined in Section 2.4. Coefficients are scaled by 100. All time-varying explanatory variables are measured in year $t-1$. Ln(Tax Loss Stock $_{t-1}$) is the natural logarithm of (Tax Loss Stock $_{t-1}$ +1) to account for zeros. All continuous covariates are winsorized at the 1st and 99th percentiles within each year. Standard errors are computed using the delta-method and are clustered at the three-digit industry level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

B Chapter 2 Appendix

Table B.1: **Sample Sizes**

Full Sample	Tax Registrants as of Jan. 2017, registered before Jan. 2016	1401838
Cut 1:	and Filed Non-Empty Financial Statements in 2016	1047818
Cut 2:	and Positive Revenue and Costs in 2016	922185
Cut 3 (Analysis Sample):	and Non-Zero Net Tax Remittance in 2016	893402

Note: These figures do not include non-business units or sole proprietors. The tax registry snapshot is as of 2017. We start by excluding firms that registered after December 2015 (to account for any delayed firm enrollment in SI) and denote this the "Full Sample". Firms are required to file financial statements with tax authorities; "Cut 1" restricts to firms that filed non-empty statements. "Cut 2" restricts to firms with positive revenue on the financial statement. "Cut 3" restricts to firms with non-zero net tax remittance in 2016. Net tax remittance is defined as the total remittance across all categories of taxes minus the sum of refunds across categories. Firms that have zero tax remittance and zero revenue on financial statements are likely non-active firms. We take Cut 3 as our analysis sample for the paper.

Table B.2: **Correlation Between Pooling Unit Budgetary Pressure and Participation Across Different SI Programs**

	Pension (1)	Medical (2)	UI (3)	Injury (4)	Maternity (5)
Ln(Budgetary Pressure)	3.351***	4.407***	3.291***	3.675***	3.849***
	(0.989)	(1.109)	(1.077)	(1.032)	(1.115)
Agricultural Pop. Share	-4.506**	-5.371**	-4.574**	-4.779**	-4.570**
	(2.000)	(2.222)	(2.008)	(2.039)	(2.024)
Migrant Share	27.163***	29.981***	29.419***	28.217***	30.051***
	(8.596)	(8.759)	(8.676)	(8.626)	(8.710)
Urban District	2.758	2.254	6.581***	3.372*	8.879***
	(2.482)	(2.244)	(1.974)	(2.011)	(2.809)
Outcome Mean	45.971	44.988	45.424	45.817	44.994
Elasticity	0.073	0.098	0.072	0.080	0.086
Number of firms	820461	820461	820461	820461	820461
Firm Size Decile FEs	✓	✓	✓	✓	✓
Firm Age FEs	✓	✓	✓	✓	✓
Industry and Owner-Type FEs	✓	✓	✓	✓	✓
Prefecture FEs	✓	✓	✓	✓	✓

Note: $*p < .1$, $**p < .05$, $***p < .01$.

C Chapter 3 Appendix

SI Contribution Deferments and Cuts in Response to Covid-19

Table C.1: **Payroll Tax Responses Around the World**

	Deferral of SSC	Rate reduction or exemptions
Argentina	Employers affected by quarantine that provide required information have March 2020 employer contributions automatically postponed to mid-June	Employers providing healthcare-related services enjoy a 95% reduction of employer contributions for 150 days after 20th March.
Brazil	March/April payment to be paid in August and October 2020, respectively.	
Czech Republic	Late payments of SSC by employers (24.8%) for May-July 2020 receive lower penalty.	
Finland		Private sector employer contribution reduced by 2.6% from 16.95% of wages paid (applicable Jun 20 to Dec 20)
France	Companies with <50 (>50) employees can postpone March-May (April-May) payment for employer and employee contribution for up to 3 months.	
German	SSC for March-May 2020 may be deferred under the end of June 2020.	
Greece	Companies in listed industries may delay payment of SSC due in March-April to September and October.	
Hungary		March-June reduction for select sectors (Hospitality, tourism; Entertainment, film industry, performing art; Sport services; Event organization; Gambling): employers exempt from normal contribution (17.5%+1.5%); employees only liable for 4% healthcare premium (instead of 18.5% SSC) On 1 July 2020, employer rate reduced to 15.5%.
Iceland	Employers may postpone payment for up to 3 payments of SSC that fall due 1 March– 1 December. All must be paid by 15 January 2021. Conditions: substantial operational difficulties; no dividend paid in 2020; no prior delinquencies or failure to file.	
Italy	Withholding tax on employment income, SSC and VAT due from enterprises in April-May 2020 (March-April for the self-employed) is deferred to 30 June.	
Japan	If a taxpayer's gross income for a period (at least one month) on or after 1 February decreases by 20% or more as compared to the previous year's corresponding period, payment deferrals are available for up to one year upon application. Deferral available for SSC as well as corporate income tax and consumption tax	
Jordan		For private sector, for a period of 3 months starting March 1, reduced SSC rate from previous 14.25% employer and 7.5% for employee to 4.25% and 1% respectively.
Lebanon	Deferral of SSC related to the first 6 months of 2020 for an additional 6 months from the original deadlines.	
Malaysia	Deferment of Monthly Tax Installment Payments including SSC: April-June for SMEs; April-September for firms in tourism	
Montenegro	90-day postponement for businesses economically affected by pandemic to pay March-May tax liabilities, including SSC.	
Netherland	Businesses facing financial difficulties as a result COVID-19 may request deferral of payment for many taxes for 3 months, including SSC. Measure retroactive as of March 12, 2020. Further deferral may be granted if taxpayer does not distribute dividends, award bonuses or redeem shares.	

Payroll Tax Responses Around the World Continued

Norway	March/April payments postponed to August; May/June payments postponed to October.	Contribution rate reduced by 4% (from 14.1%) for salary payments May-June. Some areas already benefiting from 0% rate will enjoy 4% subsidy.
Poland	Entrepreneurs in "difficult situations" may apply for 3-month deferral for February-April.	Micro-firms with up to 9 employees enjoy exemption from SI contributions for 3 months. For companies employing from 10-49 employees, 50% of SI contributions is waived.
Portugal	Reduced employer SSC for March-May payable in July-September (three instalments) or July-December (six instalments),	Reduction of employer SSC to 1/3 in March-May.
Russia	6-month deferral for March-May; 4-month deferral for June-July period All companies operating in sectors most affected by crisis (aviation, tourism, sport, culture and others) may apply for tax deferral (3 months to 1 year) or payment in instalment (3-5 years) for taxes including SI contributions.	All SMEs enjoy rate reduction from 30% to 15% for contributions on salaries exceeding the minimum statutory wage starting from Apr. 1.
Serbia	Deferral of payments of salary tax and SSC on salaries for March-May (or April-June if March salary was paid by 10 April) until January 4, 2021. Deferred tax obligations can be paid over 2 years without late-payment interest.	
Slovakia	Postponement of payment of employer contributions in case of sales decrease of more than 40%.	
Spain		Companies severely affected: for company with <50 (>= 50 workers) (as of 29-02-20), May-June contributions completely (75%) exempted; Companies less severely affected: for company with <50 (>=50) workers, for workers returning to work, 85% (60%) exemption on May's contribution and 70% (45%) on June's contribution.
Switzerland	Deferral is granted on case-by-case basis for unspecified duration; interest on late payments is suspended for 6 months. From Monday, 23 March 2020 until further notice, interest on arrears will be charged at 0% on all social security contribution claims.	
Sweden		SSC to be reduced from 31.42% to 10.21% for the period Mar. 1-Jun. 30; applies to up to 30 employees per employer and for salaries up to SEK 25,000 per month for each employee.
Thailand		The rate for employers and employees decrease from 5% to 4% for 6-months, March-August.
United States	Employer contribution to social security taxes (Mar 17 to end of 2020) can be deferred, 50% to be paid by end of 2021 and remainder by end of 2022.	
Vietnam	Suspends SSC for those who are affected by the Covid-19 epidemic until December without interest charge for late payment. Conditions: involved in passenger transport, tourism, accommodation, restaurants or other sectors where either 1) unable to find enough work for employees and 50% or more of workers enrolled in SI scheme temporarily stopped working; or 2) suffering a loss equivalent to at least 50% of total value of assets (excluding land).	

Note: This table reports Social Security Contribution (SSC) deferments and temporary cuts enacted in response to the COVID-19 economic downturn. We collected these from a wide range of sources, largely announcements by major accounting firms advising firms on the new tax measures.

Supplementary Results

Table C.2: **Sample Sizes**

Full Sample	Tax Registrants as of Jan. 2017, registered before Jan. 2016	1401865
Cut 1:	and Filed Non-Empty Financial Statements in 2016	1047818
Cut 2:	and Revenue and Costs > 10,000 CNY in 2016	902,614
Cut 3 (Analysis Sample):	and Non-Zero Net Tax Remittance in 2016	879,225

Note: These figures do not include non-business units or sole proprietors. The tax registry snapshot is as of 2017. We start by excluding firms that registered after December 2015 (to account for any delayed firm enrollment in SI) and denote this the "Full Sample". Firms are required to file financial statements with tax authorities; "Cut 1" restricts to firms that filed non-empty statements. "Cut 2" restricts to firms with positive revenue on the financial statement. "Cut 3" restricts to firms with non-zero net tax remittance in 2016. Net tax remittance is defined as the total remittance across all categories of taxes minus the sum of refunds across categories. Firms that have zero tax remittance and zero revenue on financial statements are likely non-active firms. We take Cut 3 as our analysis sample for the paper.

Table C.3: **Share of Firms by Industry, 2016**

	Provincial Admin Data	China Statistical Yearbook
Mining and washing of coal	0.02%	1.33%
Extraction of petroleum and natural gas	0.02%	0.04%
Mining and processing of ferrous metal ores	0.02%	0.50%
Mining and processing of non-ferrous metal	0.01%	0.44%
Mining and processing of non-metal ores	0.12%	0.96%
Support activities for mining	0.01%	0.04%
Mining of other ores	0.03%	0.01%
Processing of food from agricultural products	1.93%	6.87%
Manufacture of foods	1.15%	2.39%
Manufacture of liquor, beverages and refined tea	0.35%	1.84%
Manufacture of tobacco	0.02%	0.03%
Manufacture of textile	9.57%	5.22%
Manufacture of textile, wearing apparel and accessories	5.37%	4.08%
Manufacture of leather, fur, feather and related products	0.93%	2.31%
Processing timber, mf of wood, bamboo, etc	1.52%	2.41%
Manufacture of furniture	0.52%	1.53%
Manufacture of paper and paper products	1.55%	1.74%
Printing and reproduction of recording media	1.56%	1.47%
Manufacture for culture, education, & entertainment	0.83%	2.45%
Processing of petroleum, coking & nuclear fuel	0.25%	0.50%
Manufacture of raw chemical material	6.43%	6.49%
Manufacture of medicines	1.03%	1.99%
Manufacture of chemical fibers	1.18%	0.48%
Manufacture of rubber and plastics products	5.53%	4.83%
Manufacture of non-metallic mineral products	3.94%	9.25%
Smelting and pressing of ferrous metals	1.70%	2.24%
Smelting and pressing of non-ferrous metals	1.77%	1.85%
Manufacture of metal products	8.32%	5.48%
Manufacture of general purpose machinery	9.46%	6.25%
Manufacture of special purpose machinery	6.71%	4.65%
Manufacture of automobiles	3.01%	3.83%
Manufacture of transport equipment	1.49%	1.31%
Manufacture of electrical machinery	6.12%	6.23%
Manufacture of computers, communication equipment	5.23%	4.02%
Manufacture of measuring instruments and machinery	1.12%	1.15%
Other manufacturing	8.38%	0.50%
Utilization of waste resources	0.29%	0.42%
Repair of metal products, machinery	0.28%	0.10%
Electric power and heat power	0.98%	1.92%
Production and supply of gas	0.35%	0.40%
Production and supply of water	0.91%	0.46%
Number of firms	48995	378599

Note: This table compares the share of firms by industry observed in our provincial data set to national firm shares reported in the China Statistical Yearbook.

Table C.4: **Share of Firms by Ownership Type, 2016**

	Provincial Admin Data	China Statistical Yearbook
By status of registration		
Domestic funded	76.63%	86.91%
State-owned	2.06%	0.65%
Collective-owned	9.79%	0.55%
Cooperative	3.70%	0.25%
Joint ownership	0.26%	0.03%
State joint ownership	0.04%	0.00%
Collective joint ownership	0.08%	0.01%
Joint state-collective	0.09%	0.01%
Other joint ownership	0.05%	0.01%
Limited liability corporations	15.72%	25.42%
State sole funded	0.14%	0.91%
Other LLCs	15.58%	24.51%
Share-holding corporations limited	0.00%	3.17%
Private enterprises	45.22%	56.61%
Private-funded	2.07%	3.26%
Private partnerships	0.14%	0.56%
Private LLCs	42.29%	50.37%
Private share-holding corporations ltd	0.73%	2.42%
Other enterprises	0.15%	0.23%
Enterprises with funds from HMT	10.13%	6.19%
Joint-venture	2.29%	1.86%
Cooperative	0.11%	0.15%
Sole investment	3.84%	4.01%
Share-holding corporations limited	3.84%	0.13%
Other	0.02%	0.04%
Ambiguous label	0.02%	
Foreign funded enterprises	14.06%	6.90%
Joint-venture	2.40%	2.39%
Cooperation	0.09%	0.14%
Sole funds	11.26%	4.19%
Share-holding corporations limited	0.21%	0.12%
Other	0.09%	0.06%
Number of firms	48995	378599

Note: This table compares the share of firms by industry observed in our provincial data set to national firm shares reported in the China Statistical Yearbook.

Table C.5: **Decile End Points**

Revenue (CNY)

	Minimum (10,000s)	Maximum (10,000s)
0	1	12
1	12	27
2	27	48
3	48	83
4	83	141
5	141	235
6	235	404
7	404	785
8	785	2,135
9	2,135	

Note: This table contains the end points for the revenue decile bins used in Figures 4.2, 4.3 and 4.4. The maximum in the 10th decile is omitted. Revenue refers to business revenue reported on financial statements.

Table C.6: **Industry Patterns**

	% of Firms	% Paying SI	% of Total SI Payment	100 × $\frac{\text{Total Subsidy}}{\text{Total Costs}}$	Mean $\frac{100\times Subsidy}{Costs}$	100× $\frac{\text{Total Subsidy}}{\text{Liquidity}}$	Mean $\frac{100\times Subsidy}{Liquidity}$
Health and social work	0.11	78.03	0.27	1.23	2.45	2.40	6.68
Financial services	0.43	73.19	4.93	0.34	1.68	0.15	2.58
Energy and utilities	0.20	68.09	1.62	0.18	1.08	0.37	2.48
Education	0.15	60.77	0.13	1.76	3.18	2.19	8.91
Hydrolics, environment and other	0.13	59.56	0.57	0.82	1.38	0.30	1.63
Real estate	2.13	59.26	2.55	0.17	1.59	0.04	2.76
Equipment, Chemical, Metal Manuf	25.32	56.68	44.25	0.40	0.89	0.50	0.98
Textile, Food Manufacturing	8.41	52.06	8.73	0.44	0.80	0.55	1.16
Lodging and food services	1.04	47.75	1.17	1.21	1.51	1.23	4.09
Residential services	2.79	46.97	2.90	1.03	1.79	0.42	3.26
Construction	6.50	46.60	5.40	0.21	0.97	0.14	1.03
Telecommunication, software, IT	2.16	46.56	2.62	0.50	1.51	0.56	2.68
Science, research, technology	3.58	45.71	2.71	0.54	1.13	0.51	1.84
Rental and business services	8.24	45.01	7.61	0.76	1.75	0.14	3.53
Wholesale	22.30	40.63	5.73	0.09	0.58	0.17	0.85
Transportation and logistics	3.08	38.19	3.85	0.48	0.70	0.69	1.44
Retail	12.16	36.61	4.41	0.19	0.74	0.32	1.20
Culture, sports, entertainment	0.52	33.45	0.26	0.51	1.34	0.28	3.24
Agriculture, forestry, fisheries	0.73	23.26	0.27	0.17	0.45	0.16	0.47

Note: This table reports industry-level statistics on SI participation and the simulated magnitude of the SI tax cut. Column 1 reports the percent of all active firms accounted for by each industry. Column 2 reports the percent of firms that remit SI contributions. Column 3 reports the percent of total SI contributions accounted for by each industry. Columns 4 and 6 report the total implied subsidy from the SI tax cut over total costs and total liquid assets in the industry. Columns 5 and 7 report the average subsidy-to-cost and subsidy-to-liquid assets ratio among the firms in the industry after winsorizing at the 1st and 99th percentiles.

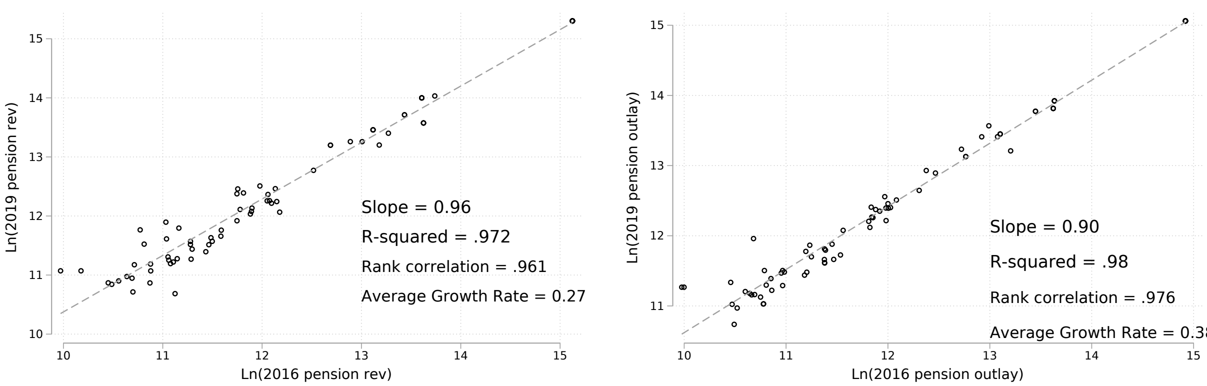
Table C.7: **Revenue Thresholds Used in Chen et al. [2020a] When Estimating Sales Declines**

	Micro	Small	Medium
Agriculture	500000	5000000	20000000
Mining	3000000	20000000	400000000
Manufacturing	3000000	20000000	400000000
Utilities	3000000	20000000	400000000
Construction	3000000	60000000	800000000
Wholesales & retail	1000000	5000000	200000000
Trans. & logistics	1000000	10000000	300000000
Hotels & catering	1000000	20000000	100000000
IT & comm tech	500000	10000000	100000000
Financial services	500000	5000000	100000000
Real Estate	1000000	10000000	2000000000
Leasing & services	500000	5000000	100000000
Sci & tech	500000	5000000	100000000
Environmental	500000	5000000	100000000
Resid. services	500000	5000000	100000000
Education	500000	5000000	100000000
Health services	500000	5000000	100000000
Entertainment	500000	5000000	100000000

Note: This table reports the revenue cutoffs used by Chen et al. [2020a] to classify firms into size bins for the purpose of estimating the change in sales due COVID-19 across industry and size bins. The revenue cutoffs correspond to the office MIIT size classification. Each column displays the right-hand end point for that bin. Firms with revenue greater than the "Medium" column are large. All values are in CNY and are applied to annual revenue.

Figure C.1: **Pension Finances by Pooling Unit in 2016 and 2019**

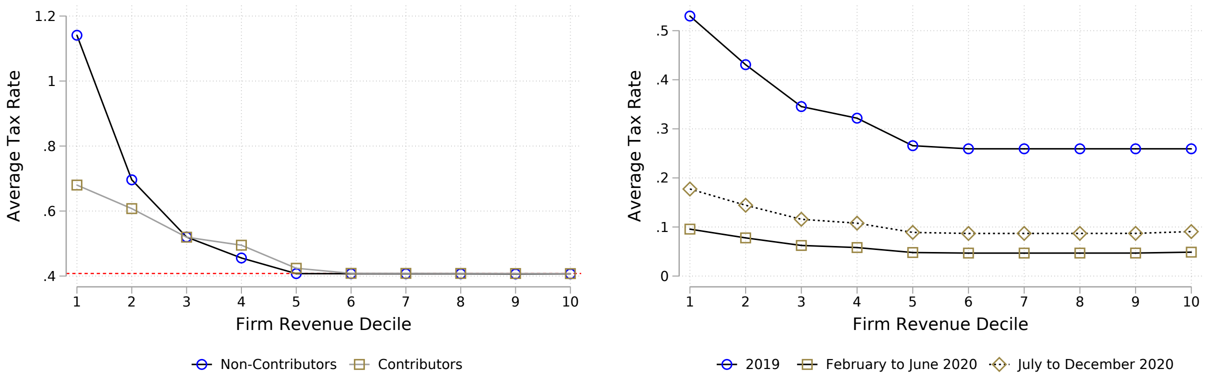
a **Local Revenues** b **Local Outlays**



Note: Panel A plots the 2016 and 2019 revenues of the BOAI pension system for each of the province's local pooling units. The slope and R-squared reported in the figure correspond to the dashed line fitted to these points. For each year, we also assign each pooling unit an ordinal rank, and report the Pearson correlation coefficient for the 2016 and 2019 ranks. Panel B repeats this exercise using local pooling unit pension outlays. Both outlays and revenues in 2019 are inflation adjusted to 2016 values, and therefore the report slope

Figure C.2: **Average Tax Rate Robustness**

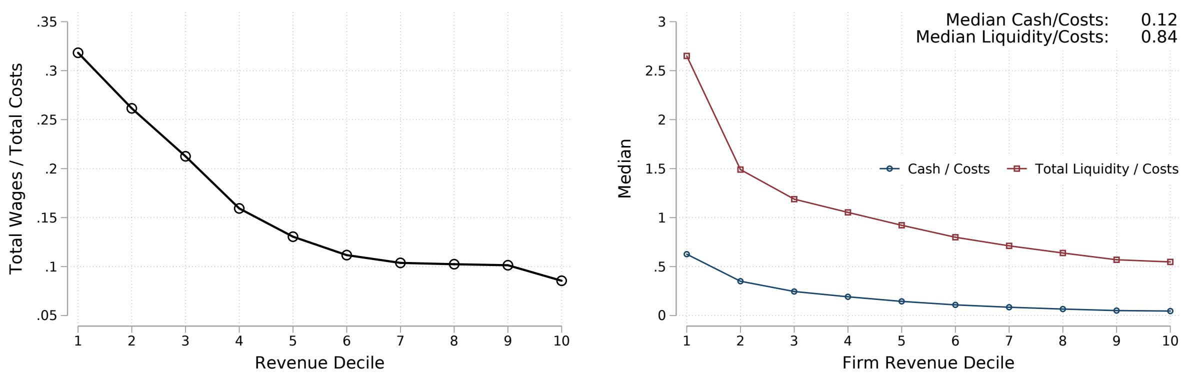
a **Average Tax Rates in 2016** b **Effect of 2020 Cuts Among SI Contributors**



Note: Panel A plots the average tax rate (ATR) for each revenue decile as follows: (1) Revenue deciles are calculated for the full sample. (2) Each decile is split into SI contributing and non-contributing firms, creating 10 × 2 bins. (3) For each bin, sum the total wages and total employees across firms in that bin (after winsorizing at the 1st and 99th percentiles). (4) Calculate the average wage as the sum of total wages over the sum of total employees. (5) Calculate the ATR for each group following the formula shown in Figure 4.1. The red horizontal line demarcates the combined statutory rate across all contribution categories in 2016. If $\sum_{i\in g} W_i / \sum_{i\in g} E_i \in [.6\bar{w}_c, 3\bar{w}_c]$, the ATR is equal the statutory rate. Panel B repeats this exercise, for contributing firms only, but applying (a) the 2019 rates, (b) the reduced rates available for February to June 2020, and (c) the reduced rates available for July to December 2020. Both panels restrict to firms with positive wages (from corporate income tax returns) and employees (from the tax registry).

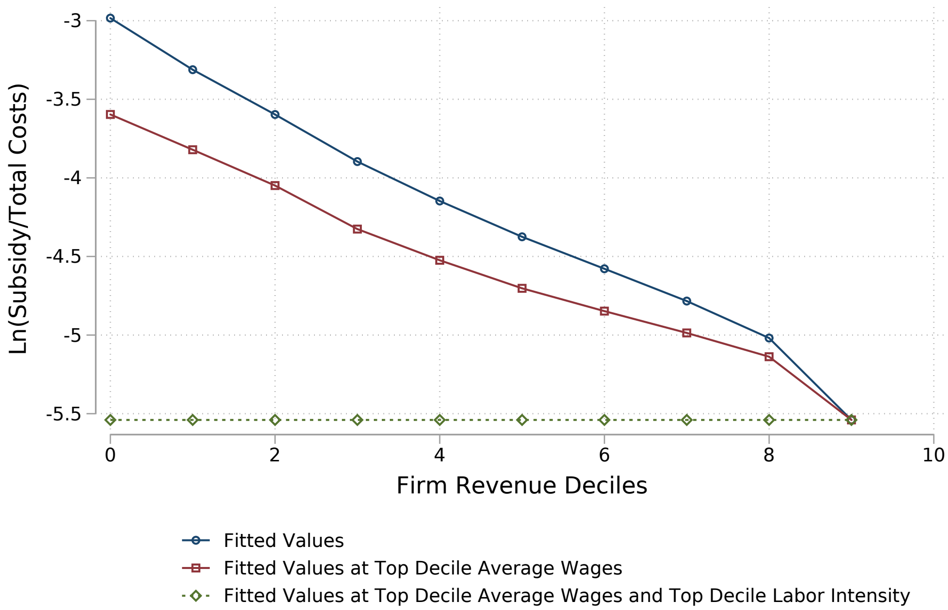
Figure C.3: **Labor Intensity and Liquidity Across the Size Distribution**

a **Labor Intensity** b **Liquidity**



Note: Panel A plots average labor intensity across the firm size distribution. For each firm, we calculate the ratio of wages to total costs. We winsorize this ratio at the 1st and 99th percentiles within each revenue decile, then take the average. Wages are as reported on corporate income tax returns. Panel B plots the median of cash-to-costs and total liquidity-to-costs ratios for each firm revenue decile. Cash holdings and total liquidity are as reported on the balance sheet. Revenue is as reported on income statements.

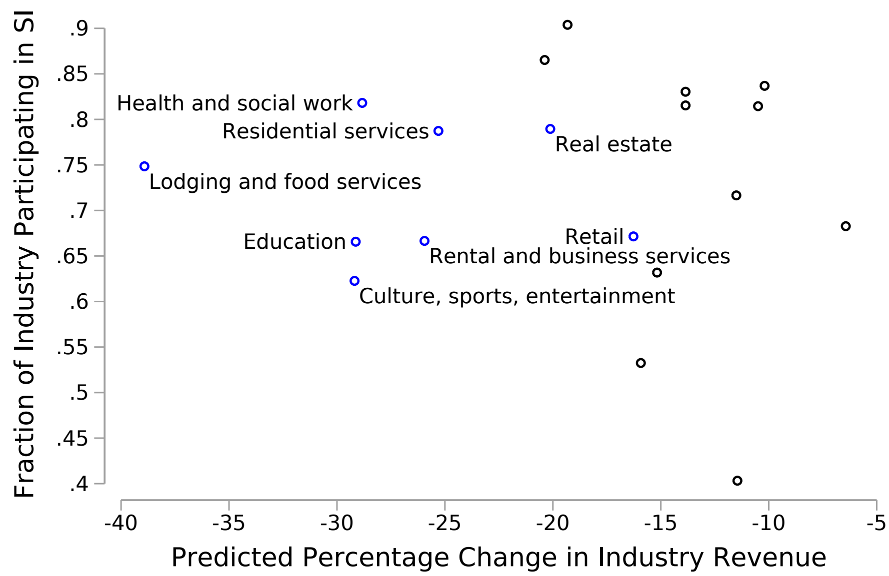
Figure C.4: **Decomposing the Size Gradient**



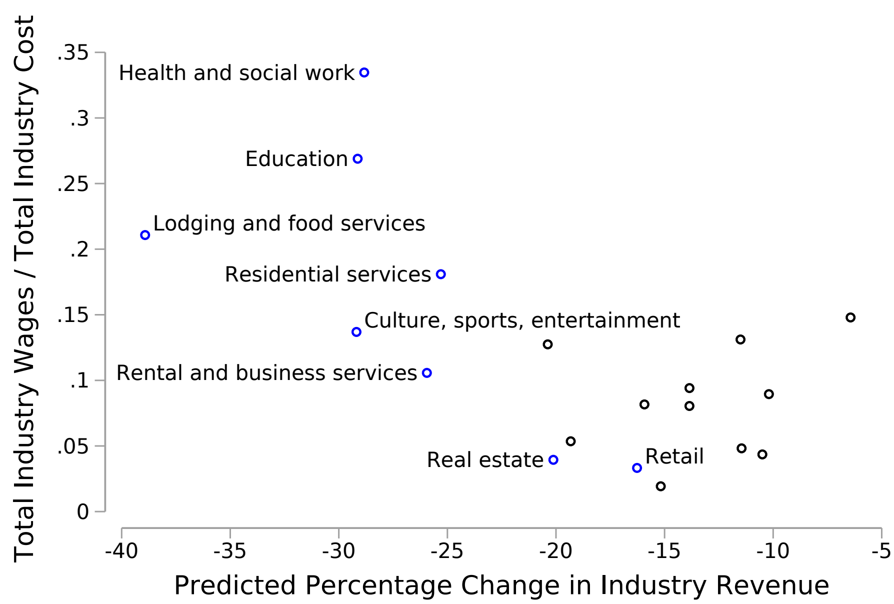
Note: This figure decomposes the size gradient of the implicitly subsidy generated by the payroll tax cuts. We regress $Ln(Subsidy) = \beta_0 + \beta_1 LI_i + \beta_2 W_i + \epsilon_i$ where LI_i is firm i's labor intensity (total wages / total costs) and W_i is the firm's average wage (total wages / employees). The first series plots the average fitted value from this regression in each firm size decile. The second series calculates the fitted value assuming W_i is the average of W_i in the top decile. The third series calculates the fitted value assuming W_i and LI_i are the average values from the top decile. Comparing the three series indicates that most of the size gradient in the subsidy over costs ratio derives from the size gradient in labor intensity, rather than the size gradient in average wages.

Figure C.5: **SI Participation and Labor Intensity versus Predicted Change in Revenue**

a **Participation**



b **Total Wages / Total Costs**



Note: This x-axis is the mean percent change in revenue caused by the COVID-19 shock estimated by Chen et al. [2020b] for the period March 26th to April 16th, 2020 (9-12 weeks following the onset of the Wuhan lock down). Using 1.5 billion VAT transactions, they report revenue changes for 4 firm size bins and 18 industries, resulting in 72 bins. The predicted percent change we plot is the cost-weighted average among all firms (in our data) in the industry. In Panel A, the y-axis is the fraction of total operating costs, in a given industry that is accounted for by SI participating firms. In Panel B, the y-axis is the ratio of total industry wages over total industry costs (labor intensity). Wages are as reported on corporate income tax returns, whereas total operating costs are as reported on financial returns.

D Chapter 4 Appendix

This appendix supplements our paper "Transitioning to Value-Added Taxes: Effects on Investment and Production" with the following sections:

- Section A provides details on the calculation of effective tax rates.
- Section B provides supplemental results.

Estimating Effective Changes in Output and Input Taxes

Consider firm i in industry j selling to customer c. The tax on this transaction depends on three parameters:

1. **Statutory Rate:** The statutory rate applied on a transaction. The statutory rate is either 3% or 5% under the BT system, and 6%, 11%, 13%, or 17% under the VAT system, depending on firm i's industry.
2. **VAT-Status of the Customer:** Customers that are firms in the full VAT system can claim credit for the tax paid on the transaction which effectively leaves the transaction untaxed. Before the 2012 reform, only the original VAT firms (manufacturing) could claim credit for taxes paid. After the 2012 reform, firms above the registration threshold of 5 million CNY in the 2012B2V industries could claim credit for taxes paid as well.
3. **VAT-Status of the Seller:** In order for a customer to claim credit for the tax paid, the seller must be able to issue a VAT invoice. Before the 2012 reform, only the original VAT firms (manufacturing) could issue invoices. After the reform, all firms under the 2012 B2V industries could issue invoices as well.

Because firms buy and sell across industries with different policy parameters, they do not face one single tax on their inputs or outputs. Therefore, we instead calculate the *average* input and output tax rates across each industries j within each group of firms: (1) 2012B2V, (2) 2016B2V, and (3) Already-VAT firms. To do so, we use information from input-output tables in 2012 to estimate the fraction of each industry j's inputs and outputs flowing to and from other industries.[96] The input-output tables allow us to proxy for this fraction by the industry-level flows.

Because the invoicing and crediting abilities differ for firms above and below the registration threshold, we also need an estimate the fraction of total input and output that derives from above- and below-scale firms in each industry. For this, we use our financial statement records.

Output Tax: Denote the statutory rate on a transaction as τ_j for industry j. Denote S_j the share of j's output that is sold to entities that cannot claim credit for the tax paid. Firms in industry j that can issue invoices for the tax paid face effective output tax of $\tau_j \times S_j$. Firms in industry j that cannot issue invoices face an effective output tax of τ_j.

We calculate S_j as follows:

[96] As an illustration, before the reform, an instrument manufacturing firm under a 17% VAT that sells to a telecommunications firm effectively faces a 17% output tax. If the same manufacturing firm instead sells to another manufacturing firm, the effective output tax is 0%. If half of the instrument manufacturer's output goes to each customer, then the average effective output tax would be 8.5%.

1. Sales to domestic final consumers are taxed. Exports are treated as untaxed. Output going to own-industry fixed capital formation is untaxed. Denote the share of industry j's output going to each as $\alpha_{j\to c}$, $\alpha_{j\to e}$, and $\alpha_{j\to f}$, respectively.

2. Denote sales from industry j to industry k as $\alpha_{j\to k}$. The fraction of $\alpha_{j\to k}$ that is taxed is ψ_k the fraction of industry k's input used by firms that cannot claim credit for the tax paid on inputs.

3. We then estimate S_j as $\sum_k \alpha_{j\to k}\psi_k + \alpha_c$.

4. Using the financial returns data to estimate ψ_k for each industry k, we estimate the share of total industry input that comes accrues to firms below the relevant VAT registration threshold for that industry: 5 million CNY for B2V reform industries, or 500,000 and 800,000 for wholesale and manufacturing. This is the share of industry k's inputs that are not creditable under the VAT, and therefore effectively taxed.

Input Tax: The input tax is calculated similarly. Denote $\alpha_{j\leftarrow k}$ the fraction of industry j's inputs that originate from industry k. Denote γ_k the fraction of industry k's output originating from firms with invoice issuing capability. Then, for firms in industry j under the full VAT system, the effective input tax is $\sum_k \alpha_{j\leftarrow k}(1-\gamma_k)\tau_k$. For firms in industry j not under the full VAT system, the effective input tax is $\sum_k \alpha_{j\leftarrow k}\tau_k$.[97]

Incorporating Voluntary Registration: We assume away voluntary registration of below-scale VAT firms. In reality, some small firms may register to become full VAT taxpayers, particularly if they purchase heavily taxed inputs.

Fully-Exempt Small Firms: As of 2013, all firms with monthly revenue below 20,000CNY, and 30,000CNY as of 2014, are completely exempted from an output tax. Such exemption applies under both the VAT and BT systems. When calculating average output tax rates, we exclude firms with 360,000 annual revenue in 2012 (30,000$\times$ 12) because these firms are excluded from our treatment and control groups in the analysis. When calculating input tax rates, these firms are included as suppliers in their respective industries k.

Results: Table 5.4 shows the estimated average tax rates for above and below threshold firms in four indusry groupings: the Already-VAT firms, the 2012 B2V reform industries, the 2016 B2V reform industries, and those industries exempt from charging output tax under both the VAT and BT.

Supplemental Results

Finally, we investigate behavior around the thresholds at 360,000 and 5,000,000.

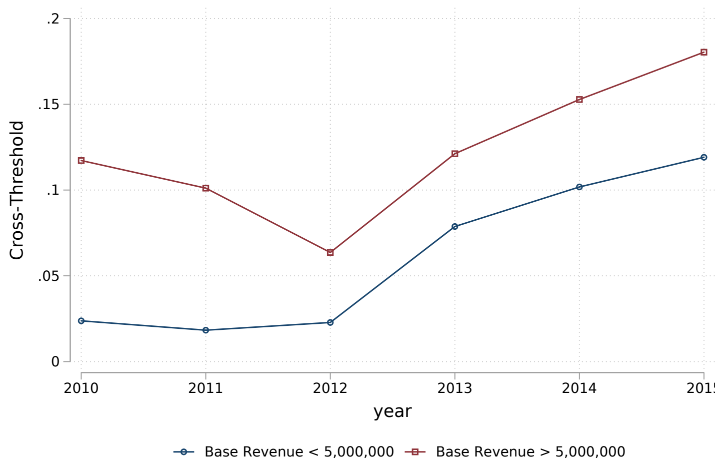
[97] We treat imported inputs as untaxed. While this is not true in reality, the tax treatment of imports did not change due around the reform period.

Table D.1: **Number of Firms per year in the Analysis Sample**

	2012 B2V Industries	2016 B2V Industries
	N	N
2010	2425	12552
2011	4259	18521
2012	5644	23337
2013	5193	21564
2014	5081	20544
2015	4863	19620
2016	4716	19312

Note: This table lists the number of firms in each year in the analysis sample described in section 5.2. There was substantial entry into the tax registry in 2010 and 2011. Firms in 2012 B2V industries that register with tax authorities after the 2012 reform are not in our data set. We artificially apply this same restriction to the 2016 B2V industries in constructing the analysis sample. This explains why the sample number of observations levels off in 2013.

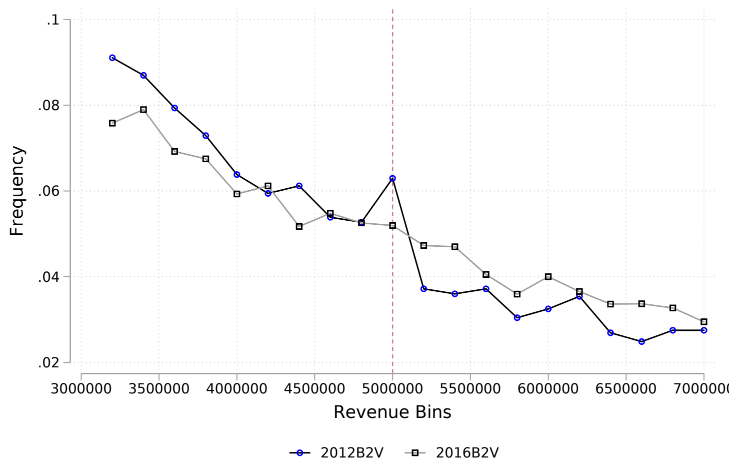
Figure D.1: **Percent of B2V Firms Crossing the Revenue Threshold**



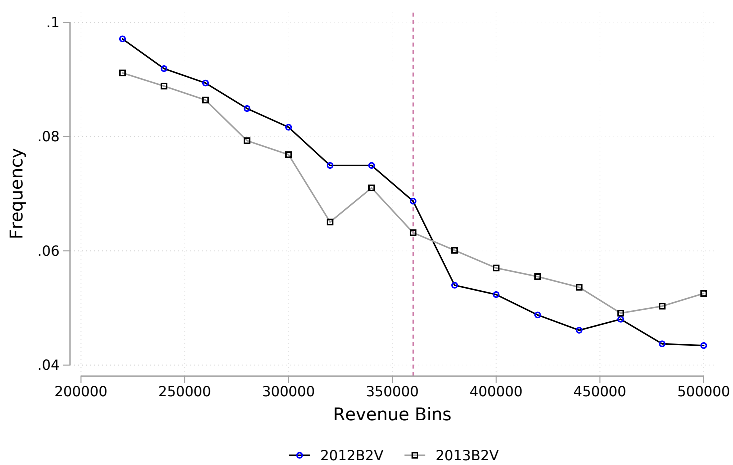
Notes: Firms are divided into above and below the 5,000,000 revenue threshold according to their average revenue in 2010-2012. It then plots the fraction in each year whose contemporary revenue is on the opposite side of the threshold.

Figure D.2: **Bunching at the Threshold**

a Bunching at Mandatory Registration Threshold

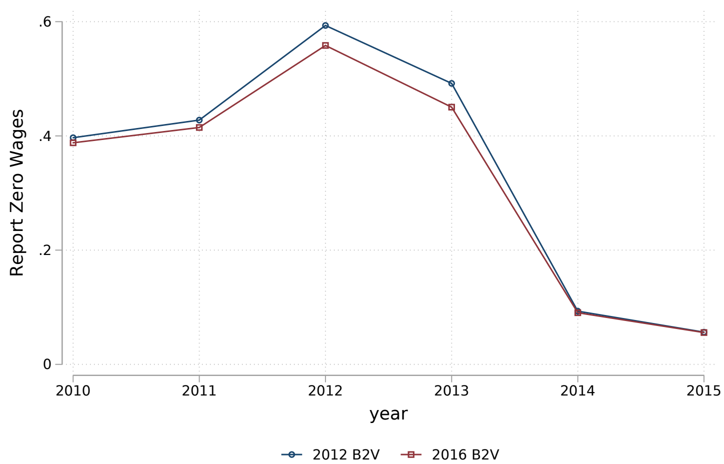


b Bunching at Micro-Exemption Threshold



Notes: This figure reports the density of firms around (A) 5,000,000 revenue, corresponding to the full VAT registration threshold, and (B) 360,000, corresponding to the micro-firm exemption threshold below which firms are exempt from both VAT and BT payments.

Figure D.3: **Report Zero Wages**



Notes: This figure plots the share of the analysis sample that report zero wages. In 2014, the quality of wage reporting increased, such that there was a dramatic reduction in zero wage reporting.