**Title**
Essays in Macroeconomics and Finance



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**Publication Date**
2011

Peer reviewed|Thesis/dissertation

**Essays in Macroeconomics and Finance**

by

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A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Economics

in the

Graduate Division

of the

University of California, Berkeley

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Fall 2011

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## Abstract

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For the past two decades, economists have focused intensive effort on building Macroeconomics on a firm Microeconomic foundation. As Macroeconomic research are more integrated with Microeconomics, more and better micro evidence has been examined to verify Macroeconomic theories. One recent development in this line of research uses detailed firm-level evidence to modify current Macroeconomic theories. In this dissertation extensive firm-level evidence are studied to shed light on important macro issues such as investment dynamics, financial frictions, regulations and productivity growth. In this study firm behaviors are studied and modeled by utilizing theories from a variety of fields in Corporate Finance, Public Finance, International Economics, Macroeconomic Dynamics etc. Implications of these evidence on the economic theory are carefully examined and subsequent extension of existing models are proposed.

This dissertation consists of three chapters. All chapters study firm behaviors and their implications on macroeconomics, however, the focus of each is different. The first chapter studies issues of credit conditions, uncertainty and investment; the second chapter (co-authored with Zhiyong An) engages the issues of taxation and international corporate finance; the third chapter show how regulations are likely impact foreign investment.

The first chapter explores the heterogeneity in firms' response to high economic uncertainty. I show that the effect of high economic uncertainty on firms' investment varies significantly with the degree of financial constraints. Firm decisions are studied in a model of non-convex adjustment costs and time-varying second moment shocks, with financial constraints. In my model, uncertainty makes financially-constrained firms cautious in capital spending and creates long periods of under-investment for these firms. Estimates from firm-level data show that publicly-traded companies' investment-to-capital ratio falls by an average of around 15% in response to a one standard deviation increase in uncertainty. Firms with easier access to credit are found to be much less responsive to uncertainty, consistent with the model's predictions. This implies that the effectiveness of stimulus policy may largely depend on firms' accessibility to credit in episodes of high uncertainty.

The second chapter (co-authored with Zhiyong An) studies how firms respond to a quasi-experiment in China. China's new *Corporate Income Tax Law* was passed in March 2007 and took effect on January 1, 2008. It increases the effective corporate income tax rate from about 15% to 25% for foreign investment enterprises (FIEs), while keeps that unchanged at 25% for domestic enterprises (DEs). This study uses a difference-in-differences approach to investigate FIEs' response to the law. Employing the Chinese Industrial Enterprises Database (2002-2008) to implement the analysis, we find evidence that FIEs are responding to the law by shifting their income out of China. Second, the magnitude of the estimated response is larger for enterprises larger in size, which suggests the greater capability of shifting income across countries for larger enterprises. In addition, the response is more acute for investment enterprises from Hong Kong, Macau, or Taiwan (HMT) than that for other FIEs, which is consistent with the tax haven status of Hong Kong and Macau.

The third chapter studies productivity spillovers to domestic firms from foreign direct investment (FDI). Such productivity gain from FDI is considered to be the basis of policies that promote FDI in many countries. In this chapter, firm-level panel data from six European countries are examined to test a number of hypotheses regarding the impact of FDI on the productivity of domestic firms. I find evidence for the backward linkage channel of the FDI spillovers. Using a new dataset, *Investing Across Borders 2010* that documents and scores regulations for FDI in 87 countries, this study goes further to explore how FDI-specific policies and institutions impact the spillovers from FDI inflows. Empirical evidence shows that good investment climate is associated with productivity gains, either by direct productivity contribution or by productivity increase in upstream industries. Higher ownership limit is shown to be significantly and positively correlated with productivity. However, productivity impact varies greatly across different investment climate measures.

# Contents

## Acknowledgments

I am very grateful to my advisors, Yuriy Gorodnichenko and Ulrike Malmendier, and committee members Bob Anderson and Dmitry Livdan for their continuous guidance, support and encouragement. I am also indebted to George Akerlof, Zhiyong An, Alan Auerbach, Nick Bloom, Steve Bond, Hui Chen, Long Chen, Luosha Du, Barry Eichengreen, Nicolae Garleanu, Pierre-Olivier Gourinchas, Kusi Hornberger, Martin Lettau, Maurice Obstfeld, Berardino Palazzo, Christine Parlour, Haonan Qu, Christina Romer, David Romer, Murat Seker, Adam Szeidl, Gewei Wang and Neng Wang for very useful comments and discussions. I would also like to thank seminar participants in Boston University, Cheung Kong Business School, Shanghai Advanced Institute of Finance at Jiaotong University, Peking University, The World Bank, Tsinghua University and University of California at Berkeley. My co-author Zhiyong An would like to thank Emmanuel Saez and Feila Zhang for helpful comments.

# Chapter 1

# Time-Varying Uncertainty and Financially Constrained Investment[1]

## 1.1 Introduction

This paper is a study of uncertainty, financial frictions and firm investment. In particular, I show that a firm's credit condition is important in determining the effect of uncertainty on its investment. In the empirical section, I find that firms' investment is much more sensitive to uncertainty if firms are financially constrained than if they are not. A model that features time-varying uncertainty, capital adjustment costs, financing costs and internal liquidity management is developed to provide an explanation for the empirical results. Due to the asymmetrical nature of financing costs, firms wait longer periods and investment largely depressed when economic uncertainty is high. The empirical results from publicly-traded firms suggest more than a fifteen percentage drop in the investment-to-capital ratio in response to an increase in uncertainty. The point to emphasize is that the magnitude of the response of investment to uncertainty depends crucially on how financially constrained a firm is. This has important implications for the effectiveness of stimulus policy in episodes of high uncertainty.

There has been a huge surge in uncertainty during the current crisis. The increase in implied stock market volatility is comparable in magnitude only to the Great Depression in the 1930s (Bloom (2009)). The meltdown of the financial system made banks reluctant to lend and limited credit conditions for many firms. Since the fourth quarter of 2007, firms have cut their capital spending drastically and aggregate fixed private investment has dropped 25%[2] in the fourth quarter of 2009. Although both high economic uncertainty

[1]This chapter is my job market paper previously circulated under the title *Time-Varying Uncertainty and Financially Constrained Investment: Theory and Evidence*

[2]Bureau of Economic Analysis (BEA)'s National Income and Product Account (NIPA) reports nominal fixed private investment for 2007Q4 and 2009Q4 of 2247.9 billion dollars and 1681.9 billion dollars, respectively.

and worsening financing constraints significantly impact the economy, how these two factors interact and how they contribute to the reduction in economic activity is not straightforward. In particular, how does a sudden rise in economic uncertainty affect firm investment if the firm faces difficult financing conditions? What if the firm has easy access to credit? Neither academics nor policy makers have a clear answer to these questions. Furthermore, the answers are of great policy importance, in light of current discussions on how to stimulate economic recovery by increasing firms' spending. Policy implications are derived from my study to contribute to this discussion.

This paper introduces a new model that incorporates a macroeconomic firm investment problem under time-varying uncertainty and a corporate finance model of investment under external financing constraints. The model is developed to study the mechanism how time-varying uncertainty and financial constraints interact with each other. It is built on the model in Bloom (2009), which features a real-option investment model with time-varying uncertainty. Using estimations from time-series data, he highlights the importance of time-varying uncertainty for the dynamics of economic activities. The study of investment under financial frictions is an area with decades of active research starting with the seminal papers by Modigliani and Miller (MM). Although time-varying uncertainty and financial constraints are important determinants of firm investment, there is little if any research trying to merge the two models. By incorporating these features simultaneously, I am able to show that financial frictions amplify the effect of high uncertainty on investment. To the best of my knowledge, this paper is the first to study the interactions of time-varying uncertainty, credit constraints and firm investment with firm-level data. The responsiveness of firm investments to uncertainty shocks depend on firms' financial constraints. The extent of this dependence is significantly larger than what has been implied by previous models.

My model features the time-varying uncertainty that has only recently been given more attention in the literature. Measured by firm-level volatility[3], there has been a drastic increase in the number of firms that experience abnormally high volatility since 2008. This supplements and confirms Bloom's (2009) finding that high uncertainty is a salient feature of the current economic recession[4]. My model features a time-varying second moment productivity process and both convex and non-convex adjustment costs on capital. Models with a non-convex adjustment cost essentially generate a region of inaction in capital spending: firms only invest when business conditions are sufficiently good and only disinvest when they are sufficiently bad. Upon the arrival of an uncertainty shock, firms expand the region of waiting–they scale back capital spending–and this behavior could lead to a sharp decline in aggregate investment.

However, Bloom's (2009) model is one of the neoclassical models that satisfy the MM

[3]The measure of the uncertainty shock is defined in Section 4.

[4]Using the S&P 100 implied volatility, Bloom (2009) shows that there was a tremendous volatility shoot-up in the recent credit crunch, the highest in the past 40 years. In terms of the effect of an uncertainty shock, Bloom (2009) argues that it has a large real impact and estimates it to be a substantial drop of around two percent of GDP with a subsequent rebound over the following six months to one year.

theory (no friction). As is well known, financial frictions play an important role in the decision process of firm investment. The current crisis also features a shortage of credit for firms, so models that analyze the current event might be incomplete without financial constraints. There is a large literature that documents the difference in investment and financially constrained and unconstrained firms. Theoretical work in corporate finance (Gomes (2001), Hennessy and Whited (2007)) show that costly external financing works as an adjustment cost that makes firms cautious and cause them to choose to spend less on capital. Instead of a model with debt contraction and equity issuance as in Hennessy and Whited (2007) and Livdan et al. (2009), my model incorporates financial frictions using the financing gap, which is defined as the difference between the funds needed and the internal funds available. In my model, financial constraints are essentially modeled as a cost function imposed on the financing gap. This cost function could be non-convex or convex. The non-convexity would mean that there is a fixed cost associated with raising external funds, whereas the linearity or convexity would make borrowing more costly as firms borrow more. Such models provide a way to capture the cost of raising external finance without the complication of bond and equity finance (Whited (2006), Riddick and Whited (2009)), with cash holding as an additional state. Essentially this model features two different types of adjustment costs: costs of capital adjustment and costs of external financing. I show that adding external finance makes firms more cautious, amplifying the real-options effect that further expands the inaction region of under-investment. However, the external financing cost is different from the investment adjustment cost, as it amplifies the real-option effect in an asymmetric way: it depresses investment but not disinvestment. Since the investment decisions depend on both the capital-adjustment cost and external-financing cost, the magnitude of real-option under-investment will depend on the size of these costs. Comparative statistics from this model add insight to how these costs impact investment. Moreover, with a feature of cash holdings, this model offers a theoretical examination of optimal corporate cash holdings and risk management under different levels of uncertainty; these are issues that have not been well understood so far (Froot et al. (1993), Bates et al. (2009) and Bolton et al. (2010b)).

This paper highlights the amplification mechanism of the time-varying uncertainty and financial frictions on firm investment. The following implications and predictions are derived from my model: firms that are more financially constrained experience a larger expansion of the investment inaction region under uncertainty shocks. In contrast, financially-unconstrained firms tend to adjust investment more frequently and appear less responsive to uncertainty shocks. Financially-constrained firms also face longer investment contraction than unconstrained firms. Another implication is that financially constrained firms, more reluctant to pay the costs to raise external financing in the future, will hold more liquid assets in episodes of high uncertainty. These predictions are conducive to empirical research. It is much easier to use proxies for financial costs than for capital adjustment costs[5]. There is

[5] Cooper and Haltiwanger (2006) construct a structural investment model with capital adjustment costs. They estimate various cost parameters by matching model moments with moments from panel-level data.

a commonly-used set of measures for financial constraints. The estimated coefficients across different subsamples are evaluated to determine the impact of financial constraint on the uncertainty-investment relationship.

The predictions from the model are confirmed in the empirical results from the firm-level data. For each firm-year, I construct the measure of uncertainty as the standard deviation of daily stock returns, a measure used by Leahy and Whited (1996) and Bloom et al. (2007). Empirical results show that the investment-to-capital ratio of publicly-traded companies drops by an average of 15% in response to a one standard deviation increase in uncertainty. The drop in the growth rate of investment-to-capital ratio is around 50%. Common measures of financial constraints from the corporate finance literature are adopted (Fazzari et al. (1988), Whited (1992), Kaplan and Zingales (1997)): firm size, bond rating, dividend payout and Kaplan-Zingales index. I find that investment from firms with easier access to credit (larger firm size, existence of bond rating and higher dividend payout) is much less responsive to uncertainty. This result is consistent with my theory that firms with a lower cost of external financing tend to show smaller real-option effects and are less affected by uncertainty shocks.

This paper contributes to the current debates about the effectiveness of the fiscal stimulus. The time-varying uncertainty and the real-option theory suggest that, in episodes of high uncertainty, the inaction zone expands by a significant amount so that it is less likely for firms to reach the investment bound. By assuming that the stimulus works as a demand or productivity shock to firms, such policies will be less effective than in normal times because it will take a lot more to move firms out of the inaction zone when uncertainty is high. However, the policy implication of this study is that the effectiveness of the stimulus may depend on how financially constrained firms are. If firms are financially constrained, then the real-option effect will be largely amplified. During the current crisis, the cost of external financing has been prohibitively high, which makes the stimulus much less effective. In addition, because of the heterogeneity from financial constraints, policies could be customized differently for constrained and unconstrained firms. The model also indicates that an improvement in credit conditions could help to catalyze firms' response, especially in an episode of high uncertainty. This could be especially effective for financially constrained firms. To this end, this paper could validate the creation of the Term Asset-Backed Securities Loan Facility (TALF) in November 2008, which helps to provide credit to small businesses by supporting the issuance of loans guaranteed by the Small Business Administration (SBA)[6].

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[6]Federal Reserve Governor Elizabeth A. Duke in her February 26, 2010 testimony stated:

> "...the TALF program has helped finance 480,000 loans to small businesses ... and 100,000 loans to larger businesses ... About half of the SBA securities issued in recent months–corresponding to roughly $250 million in loans a month–were sold to investors that financed the acquisitions in part with TALF loans ... Thus, the TALF and other Federal Reserve programs provided critical liquidity support to the economy until the financial system stabilized ... credit conditions for many

By providing direct liquidity to financially constrained firms, the Federal Reserve Bank could make those firms' credit constraints less binding. My model suggests that such an injection of liquidity could make credit constrained firms invest more and become more responsive to stimulus policies. Moreover, when uncertainty is high, financial friction may amplify the real option effect to make firms invest even less. Therefore, in recessions with high uncertainty, it could be important to launch such a liquidity-provision policy along with any stimulus policy.

The rest of the paper is organized as follows. I summarize the related literature in Section 2. Section 3 presents a model, its solutions, and predictions. The empirical results are presented in Section 4. Section 5 provides policy implications and concludes.

## 1.2 Related Literature

This paper is related to two strands of literature: literature studying firm investment dynamics under macroeconomic uncertainty and literature in corporate finance studying investment under financial constraints.

The literature on firm production under uncertainty lays the foundation of this analysis, in particular the real options effect (Dixit and Pindyck (1994)). Because of the irreversibility of the investment, an inaction zone is created so that firms invest only when productivity[7] reaches an upper bound (sufficiently good), disinvest only when productivity reaches a lower bound (sufficiently bad) and do nothing if productivity is in the middle. The theoretical comparative statistic of a rise in uncertainty would be associated with an expansion in firm investment. In the models where the marginal revenue product of capital is convex, an increase in uncertainty has a positive effect on investment (Hartman (1972), Abel (1983)). Caballero (1991) shows that the sign of the uncertainty-investment relationship largely depends on the degree of decreasing marginal return to capital. Hassler (1996) and Bloom (2009) study time-varying uncertainty in a real option framework. Bloom (2009) finds that the real-option effect of aggregate investment is large either with or without the Abel-Hartman effect. I extend his firm production models to include firms' financing behavior and external financial constraints to study how financial frictions contribute to the real-option effects.

> small businesses are likely to remain challenging this year (2010). That is why the Federal Reserve has been placing particular emphasis on ensuring that its supervision and examination policies do not inadvertently impede sound small business lending. If financial institutions retreat from sound lending opportunities because of concerns about criticism from their examiners, their long-term interests and those of small businesses and the economy in general could be negatively affected, as businesses are unable to maintain or expand payrolls or to make otherwise profitable and productive investments."

[7] Productivity could reflect both technology and demand shocks.

Uncertainty has long been a subject of interest, and its relationship with corporate investment has been studied by many. Leahy and Whited (1996) is the first paper to explore empirically the relationship of uncertainty and investment. Using a dynamic panel regression technique, they find no evidence that uncertainty has an impact on investment. However, Bond and Cummins (2004) and Baum et al. (2008) find evidence that uncertainty affects investment. This paper also studies the correlation between uncertainty and investment. My results generally support those of Bond and Cummins (2004) and Baum et al. (2008) and go further to show that the magnitude of impact is different across different subgroups. Bloom et al. (2007) and Bloom (2009) show, both theoretically and empirically, results on how uncertainty reduces economic activities. I extend their work by showing both theoretically and empirically that financial frictions play an important role on firms' investment responsiveness to uncertainty shocks.

Research in corporate finance has been studying how financial frictions affect firm behavior, primarily investment behavior under the Modigliani-Miller (1958) framework. Notable research includes Fazzari et al. (1988), Gilchrist and Himmelberg (1995), Kaplan and Zingales (1997), Gomes (2001), Malmendier and Tate (2005) and Hennessy and Whited (2007). This paper contributes to the corporate finance literature by showing how this investment-financial friction relationship is further complicated by the time-varying uncertainty. I also show that this additional relationship is important for firm investment.

My model combines different features of the models in Bloom (2009) and Riddick and Whited (2009). Cash savings and external financing costs are constructed based on Riddick and Whited (2009) and a modified version of time-varying second moment process is from Bloom (2009). Such a model allows me to ask questions that are different from those two papers. Bloom (2009) is among the first to analyze the effect of uncertainty shocks on real economic activities, such as investment. My model extends his analysis to include financial constraints, because financial constraints provide interesting heterogeneity in the analysis of firm investment decisions.

Riddick and Whited (2009) study corporate saving in their paper. Although they have uncertainty in their model, there is no dynamics in uncertainty–This makes their model difficult to match with the time-varying uncertainty which the current crisis features. Whited (2006) is another paper closely related to this paper. Whited finds in micro data that the presence of financial constraints lowers a firm's investment hazard. In other words, external financing constraints tend to work as additional costs of adjustment and contribute to the real-options effect of investment. Therefore, firms with easier access to credit appear to bear lower total costs[8] of adjustment and respond more frequently to business conditions. Whited's work presents both a model and evidence of how financial frictions add to the total adjustment cost of investment for firms.

[8]Total costs include both capital adjustment cost and financing cost.

## 1.3 Model

In this section, I develop a discrete time and infinite horizon partial equilibrium model of dynamic decisions in capital spending, saving, and external financing. My model is a combination of models with elements of uncertainty shocks (Bloom et al. (2007), Bloom (2009)) and models with financial constraints (Whited (2006), Riddick and Whited (2009)). First I describe my assumptions on productivity and financing. Then I solve it using dynamic programming and discuss the optimal policy functions.

### Technology

A risk-neutral infinite-horizon firm owns and uses capital $K_t$ along with a variable factor of production $L_t$ to produce output. It faces technology, productivity and demand shocks, which is captured in $A_t$. In a manner similar to Cooper and Haltiwanger (2006), I assume that it incurs no cost when adjusting the variable factor, so I can optimize out this variable factor without the loss of generality. I assume concavity in the profit function $\pi(A_t, K_t)$, either because of decreasing-return-to-scale in production, downward-sloping demand curve, or both. The profit function takes the form of $A_t K_t^\theta$, where $\theta$ determines the level of concavity.

$$\pi(A_t, K_t) = A_t K_t^\theta \tag{1.1}$$

The logarithm of productivity follows an AR(1) process, where $A_{t+1}$ denotes the state of productivity next period. To incorporate time-varying uncertainty in the model, I specify an AR(1) process with a time-varying standard deviation:

$$log(A_{t+1}) = \mu + \rho log(A_t) + v_t, \quad v_t \sim N(0, \sigma_t^2) \tag{1.2}$$

For simplicity the stochastic volatility process follows a two point Markov Chain switching between low uncertainty $\sigma_L$ and high uncertainty $\sigma_H$

$$\sigma_t \in \{\sigma_L, \sigma_H\}, \quad where \quad Pr(\sigma_{t+1} = \sigma_j | \sigma_t = \sigma_k) = p_{k,j}^\sigma \tag{1.3}$$

In every period, firms make investment decisions at the capital price of unity; the law of motion for capital stock is as follows:

$$K_{t+1} = (1 - \delta)K_t + I_t \tag{1.4}$$

Consistent with Cooper and Haltiwanger (2006) on the capital adjustment cost, the model assumes both convex and non-convex capital adjustment costs. The assumption that the fixed cost is proportional to capital is to ensure that firms do not grow out of the fixed cost.

$$C(I_t, K_t) = \mathbf{1}\{I_t \neq 0\}\psi_0 K_t + \frac{\psi_1}{2}\left(\frac{I_t}{K_t}\right)^2 K_t \tag{1.5}$$

## Financing

Following Riddick and Whited (2009), the firm can hold cash, $P_t$, via a riskless one-period discount bond that earn interest $r(1-\tau)$. This cost $\tau$ could either reflect tax penalty on cash relative to interest income (Graham (2000), Faulkender and Wang (2006), Whited (2006)) or agency costs associated with free cash (Jensen (1986), Eisfeldt and Rampini (2009), Bolton et al. (2010b)).

I define the financial gap as the difference between the cash spending (both capital spending and saving for the future) and internal cash:

$$g(K_t, K_{t+1}, P_t, P_{t+1}, A_t, \sigma_t) = \frac{P_{t+1}}{1+(1-\tau)r} + K_{t+1} - (1-\delta)K_t + C(I_t, K_t) - (1-\tau)\pi(A_t, K_t) - P_t \tag{1.6}$$

One can think of (1.6) as a dividend when $g_t < 0$ and equity issuance when $g_t > 0$. Firms have to raise external funds to fill this gap. It is costly to obtain external financing, when the financing gap is greater than 0: $g_t > 0$.

The adjustment cost of external financing $\phi(\cdot)$ is a function of the financing gap $g_t$. I assume a fixed, linear and quadratic cost:

$$\Phi(g_t) = \left(\lambda_0 + \lambda_1 g_t + \frac{1}{2}\lambda_2 g_t^2\right)\mathbf{1}\{g_t > 0\} \tag{1.7}$$

When $g_t < 0$, firms pay out cash and I assume that there is no cost for distribution. Such a construction of financial constraint is similar to Whited (2006) and Riddick and Whited (2009). Because most financial constraints are various costs imposed on the financial gap, they argue that it does not affect the qualitative outcome of the model. In such a model with internal funds, I expect to see that firms accumulate cash reserves to avoid future cash stock-outs and costly external finance.

Define the net dividend as the dividend payout $(-g_t)$ minus the adjustment cost $\Phi(g_t)$.

$$d_t \equiv -g_t - \Phi(g_t) \tag{1.8}$$

## Firm Maximization Problem

Firms maximize all future discounted net dividends subject to the driving process of technology (1.2) along with uncertainty (1.3), the law of motion for capital stock (1.4), with equations for net dividend and profit (1.5), (1.6), (1.7), (1.8).

$$\max_{\{I_i, P_{i+1}\}_{i=1}^{\infty}} E_t \left\{ \sum_{j=0}^{\infty} \frac{d_{t+j}}{(1+r)^j} \right\} \tag{1.9}$$

## Dynamic Program

Because of the non-linearity of the problem, with the non-convexity in capital expenditure and external financing, the firm problem needs to be solved numerically by dynamic programming. As a first step, I formulate the problem as a Bellman equation. There are four state variables to keep track of: $A, K, P$ and $\sigma$. The next period's values are denoted as $A', K', P'$ and $\sigma'$. $K$ and $P$ are endogenous states, while the dynamics of $A$ and $\sigma$ are determined exogeneously. The firm chooses $(K', P')$ each period to maximize the sum of expected future cash flows, discounted by $r$. So the value function is as follows; the motions of $A$ and $\sigma$ are described the above.

$$V(K, P, A, \sigma) = \max \left\{ V^i(K, P, A, \sigma), V^n(K, P, A, \sigma) \right\} \tag{1.10}$$

where $V^i$ denotes the value with investment and $V^n$ is the value without investment. The net dividend term denotes a distribution of funds such as dividend payout ($g < 0$) or an influx of funds such as equity issuance ($g > 0$). It is the dividend payout minus adjustment cost.

$$d(K, K', P, P', A, \sigma) \equiv -g(K, K', P, P', A, \sigma) - \Phi\left(g(K, K', P, P', A, \sigma)\right) \tag{1.11}$$

Their Bellman equations are as follows:

$$V^i(K, P, A, \sigma) = \max_{K', P'} \left\{ d(K, K', P, P', A, \sigma) + \frac{1}{1+r} EV\left(K', P', A', \sigma' | A, \sigma\right) \right\} \tag{1.12}$$

$$V^n(K, P, A, \sigma) = \max_{P'} \left\{ d(K, (1-\delta)K, P, P', A, \sigma) + \frac{1}{1+r} EV\left((1-\delta)K, P', A', \sigma' | A, \sigma\right) \right\} \tag{1.13}$$

$$s.t$$

$$\log(A') = \mu + \rho \log(A) + v, \quad v \sim N(0, \sigma^2) \tag{1.14}$$

$$\sigma \in \{\sigma_L, \sigma_H\}, \quad where \quad Pr(\sigma' = \sigma_j | \sigma = \sigma_k) = p^{\sigma}_{k,j} \tag{1.15}$$

This model satisfies the conditions ensuring a unique optimal policy function, $(K', P') = policy(K, P, A, \sigma)$, if $V^i$and $V^n$ are weakly concave in $K$ and $P$ (Theorem 9.6 and 9.8 in Lucas and Stokey (1989)).

## Solution

I solve the problem numerically and investigate the relationship among optimal firm investment, time-varying uncertainty and financial constraints under reasonable parameter choices. I first describe each parameter for the baseline model and then explain the property of policy functions of firm investment. Simulations later using those policy functions show the optimal responses of firm investment to an uncertainty shock, for financially-constrained and unconstrained firms.

The model parametrization are based on previous literature and are listed in Table .1. $\theta$ in the profit function is calibrated at 0.75, from the estimates of labor shares. Consistent with Cooper and Haltiwanger's (2006) estimates from plant-level data, I choose the persistence of technology process to be 0.885. The drift of the process, the low and high value of levels of uncertainty and the transition probabilities between the low and the high uncertainty regimes are from Bloom's (2009) estimations using aggregate series. The value of high uncertainty is restricted to be twice the value of low uncertainty in the estimation. These parameters reflect key characteristics of the underlying driving process. Especially when the uncertainty regimes switch from one to the other, the parameters play a critical for calculations of conditional expectations of future profitability and variability that determine firms' optimal investment response.

Cooper and Haltiwanger (2006) find evidence that both convex and fixed cost of capital adjustment affect plant-level investment. The coefficients $\psi_0$ and $\psi_1$ are set equal to 0.039 and 0.049 to be consistent with their estimates. The depreciation rate is 0.12, a common calibration in the literature. Hennessy and Whited (2007) constructed and estimated the fixed, linear and quadratic cost of financial adjustment. I set $\lambda_0$, $\lambda_1$ and $\lambda_2$ to be 0.389, 0.053 and 0.0002 based on their estimates of the costs of external equity finance for large firms. Hennessy and Whited (2007) show that 0.389 implies a fee of $\$50,332$ for the first million dollars of gross equity. Discount rate and tax penalty rate are 4% and 5%, consistent with previous literature.

I set finite set space for numerical solutions and value function iterations. 50 grid points are used for each variable in $(K, K', P, P', A)$ for numerical solutions[9]. In order to make $V^n$ stay on grid, I adopt the grid choices for capital from Riddick and Whited (2009): $\left[(1-\delta)^j \bar{K}, ..., (1-\delta)\bar{K}, \bar{K}\right]$. For the productivity process, I use the technique in Tauchen (1986), and Adda and Cooper (2003) to form a Markov-chain estimate of the AR(1) process with time-varying uncertainty. This paper primarily uses the quadrature constructed by Tauchen (1986) extended to include time-varying uncertainty. In Appendix A, a quadrature based on Adda and Cooper (2003) with time-varying uncertainty is also constructed.

[9]Because there are 6 variables (4 states and 2 choices), I make uncertainty binary states. In this case, a matrix is created with $50 \times 50 \times 50 \times 50 \times 50 \times 2$ entries for each iteration.

## Optimal Investment Policies

Given the solutions of the model, it is interesting to see how optimal investment changes across a variety of specifications for financial constraints and different levels of uncertainty. As it is well known, the investment function should be a smooth function of productivity $A$ without capital adjustment costs. With fixed capital adjustment costs, there will be an inaction zone–a range of $A$ in which investment is equal to zero.

How does the investment-productivity relationship change with financing cost? First, the hypothetical case in which there is only a fixed cost of external financing and no liquidity buffer (zero cash holding) is studied. This case corresponds approximately to external financing in the form of equity finance when there is a large flotation cost associated with it. From Figure .1, I observe different inaction zones for different cost specifications. The smooth line is the investment policy function with no adjustment cost. The first line with the jump is the investment policy function associated with a fixed capital adjustment cost equal to 5% of the value of its average capital stock. The three lines to the right of that line are the cases where there is an additional 5%, 10% and 15% for external financing costs. One observes in this case that the inaction zone is wider with higher financing cost. Thus, financial frictions lead to less investment on average. One important feature of financial constraint is that it extends the inaction area only to the region of investment to the right. The disinvestment region does not expand. Such an effect is different from the capital fixed cost: when the capital fixed cost increases, the band widens on both sides. This is because the capital adjustment cost often shows some degree of symmetry, in the sense that a cost is incurred when firms are buying or selling capital[10].

Such an effect on investment is most severe when there is a limited amount of cash reserves. Figure .2 shows that, with more corporate saving, investment is less constrained. Lines from right to left are from the least amount of cash (zero cash) at the beginning of the period to a high level of cash reserves.

The pattern changes when cash holdings are introduced. A sufficiently large liquidity buffer, however, provides leeway in capital spending. With the fixed financing cost combined, firms will find it costless to spend up to their cash reserves, but any amount of investment greater than that will result in financing costs. Therefore, if the cash reserves are sufficiently large, there will be an additional range of productivity for which a flat investment policy function is observed in Figure .3; and this region might not coincide with the investment inaction zone.

The analysis above indicates that fixed a financing cost further constrains investment in two ways. First, it induces a wider inaction region on capital expansion, but a small asymmetric effect on capital contraction. Second, it creates more inertia in capital spending, which further exacerbates underinvestment. Corporate saving alleviates this problem–with more liquidity, the inaction and inertia regions shrink.

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[10] Firms may face higher costs in contracting than in expanding capital stock, as in Abel and Eberly (1994, 1996).

Figure .4 presents the financially constrained investment under the regime of low uncertainty (top graph) and high uncertainty (bottom graph). More capital spending is observed when uncertainty is mild; the inaction region is also smaller. The position of the lines without capital adjustment cost does not start out differing much, suggesting that capital adjustment costs alone contribute little. However, when the financial cost is taken into account, the investment inertia is greatly amplified. The boundary of the investment inaction region is pushed far along the horizontal axis due to the large financing cost.

This observed pattern is consistent with the real-option theory. Appendix B shows that, under a simple continuous-time specification, the expansion of the investment inaction region in response to a rise in uncertainty is larger for a higher adjustment cost. Therefore, the following graphs appear to illustrate a feature of real-option models: higher financing costs lead to longer periods of wait-and-see for capital expansion. It is also interesting to observe that, since financing costs are absent for capital contraction, there is no change in the lower bound of the investment inaction region.

## Optimal Financing Policies

Why firms hold unproductive cash is puzzling. First, I use Riddick and Whited's (2009) explanation to underline the role of financing cost in determining corporate saving. Taking the derivative of the Bellman equation (1.12) with respect to financing gap $g$ and applying the envelope theorem leads to the following equation:

$$1 + (\lambda_1 + \lambda_2 g)\mathbf{1}\{g > 0\} = \frac{1 + r(1-\tau)}{1+r} \int (1 + (\lambda_1 + \lambda_2 g')\mathbf{1}\{g' > 0\})\, dg'$$

If there is no financing cost, the cash holding discount $\tau$ ensures that corporate saving will be zero. Moreover, as Riddick and Whited (2009) argued, corporate saving reflects too many factors for a thorough analysis. There is no robust pattern regarding corporate saving–it could be hump-shaped or decreasing with respect to productivity. The pattern would depend on characteristics of the firm such as size. Interestingly, Riddick and Whited find that there are two effects governing the behavior of corporate saving. One effect, which they call the income effect, reflects the extra cash inflow associated with higher productivity. Another effect, the substitution effect, is defined as the substitution between cash saving and capital spending. Figure .5 shows, that under high uncertainty, firms hold more liquidity for all levels of productivity. Moreover, firms under high uncertainty appear to be more cautious, hoarding more cash and restraining themselves from capital spending.

## Simulation and Predictions of the Dynamics

To study the impact of a sudden rise in uncertainty, I use the model solutions to simulation an investment response for one representative firm. If only one firm makes a real option investment choice once every year, then there will be many investment with zero value. However, the lack of zeros in the firm-level data would reject any real-option theory. To this end, firm-level aggregations are used in previous literature. In this study I assume that each firm has 300 production units. For each category, I run simulations for 300 units for 20 years at an annual frequency, with a burn-in period of 180 periods to ensure that they are in a steady state. The responses of investment are plotted in Figure .6. After an uncertainty shock (year 0), the financially constrained firms experience large investment drops, while investment from the financially unconstrained firms quickly bounces back with a smaller initial drop. This would predict a larger investment drop and longer under-investment for financially constrained firms.

The model with both time-varying uncertainty shocks and financial constraints provides comparative statistics of the investment-uncertainty relationship across firms with heterogeneous external financing constraints. The rest of this paper explores firm-level data to test the model predictions. The main prediction is that investment from firms that face higher costs when raising external funds (thus more credit constrained by definition) will fall more when uncertainty increases sharply. For firms that face smaller costs to obtain external financing, the magnitude of the response will be smaller. This result highlights the amplification effect of financial frictions for the investment response to an increase in uncertainty.

## 1.4 Empirical Results

This section studies the investment response to uncertainty for publicly-traded companies. By using different measures of financial constraints, robust results are observed across different sample splits.

### Data and Summary Statistics

The sample contains US non-financial firms in the 2010 Compustat industrial files. The firm-level data constitutes an unbalanced panel from 1971 to 2009. The Compustat data is augmented with standard deviation of daily stock return data from The Center for Research in Security Prices (CRSP) data.

I drop firm-year observations from my sample with missing or negative values for total asset and firms that have observations for less than three consecutive years. I delete all firms whose primary Standard Industrial Classification (SIC) code is between 4900 and 4999, between 6000 and 6999, or greater than 9000, because this model of investment is inappropriate for regulated and financial firms. Observations for firms involved in significant mergers and acquisitions (greater than 15% of book asset value) during a year are also excluded. The replacement value of capital stock is constructed using the perpetual inventory method described in Salinger and Summers (1983) (See Appendix C for details). Firm investment (capital expenditure), cash flow and cash holding by the replacement value of capital stock at the end of last fiscal year are normalized. All the variables are winsorized 1% on both ends of the distribution. I construct an average measure of Tobin's Q[11] (Hayashi (1982)) by dividing the market value by the capital replacement value.

## Firm-Level Uncertainty

Uncertainty comes in many forms. When firms make investment decisions, the future productivity, price, wage, demand, regulations, exchange rates and taxes are all uncertain. An ideal measure of uncertainty would combine all those elements. The uncertainty I try to capture attempts to reflect future expectations. Following Leahy and Whited (1996), Bond and Cummins (2004), and Bloom et al. (2007), I argue that the volatility of a firm's securities summarizes the firm's uncertainty. The advantage is that, since this is a stock market-based measure, it reflects all information investors care about and it is forward-looking. Since the uncertainty I am measuring is related to information in the future, it is important to exclude ex-post information. Implied-volatility is another natural measure of that, but limitations in data availability prevented me from constructing uncertainty based on that. Instead, I have sufficient dis-aggregate and high frequency data from CRSP stock price data. Under the assumption that a company's stock price reflects information regarding all the uncertainty listed above, I can construct a general measure of uncertainty. My measure of uncertainty deviates from Leahy and Whited (1996) and Bond and Cummins (2004) because of the concern about the normalization of the uncertainty by the market debt-to-equity ratio (See Appendix C for details). Nevertheless, a measure of uncertainty using normalization of the book debt-to-equity is used for robustness checks.

The downside of this measure of uncertainty is that it is noisy. It may depart from fundamental economic uncertainty due to a variety of observations in the market, such as bubbles, noise trading, etc. To address this concern, I take the difference between the daily return and the S&P 500 market return to control for the aggregate market bubble, panic and noise. I also construct measure of uncertainty based on monthly stock returns, which might be less affected by market irrationalities than high-frequency data. Bond and Cummins (2004) study three uncertainty measures: volatility from daily stock returns (the measure I use), disagreement among securities analysts on future profitability, and the variance of forecast errors. They show that all three measures are positively correlated; to some extent, they all capture the underlying movements in uncertainty. Their results indicate that this measure of uncertainty, despite its noise, reflects the economic uncertainty I deem important.

[11]It is important to include a measure of Tobin's Q, which captures all future profitability for a firm.

## Specification

I begin my analysis by estimating the standard model[12] to identify the impact of uncertainty on investment.

$$\left(\frac{I}{K}\right)_{it} = \gamma\sigma_{it} + \alpha\left(\frac{I}{K}\right)_{it-1} + \beta X_{it} + \zeta_i + \eta_t + \epsilon_{i,t}$$

The above model determines investment rate $\left(\frac{I}{K}\right)_{it}$ as a function of its lag $\left(\frac{I}{K}\right)_{it-1}$, the level of its uncertainty $\sigma_{it}$, and control variables $X_{it}$. Year dummies $\eta_t$ are included. To control for time-specific effects. The model also fixes for firm-specific effect $\zeta_i$. Three estimation strategies are used: OLS, fixed effect, and dynamic panel regression (Holtz-Eakin et al. (1988), Arellano and Bond (1991), Bond (2002)). Dynamic panel regressions are used to partly address the endogeneity concern–it allows the regressors to be endogenous. In addition, this estimation first-differences all the variables for GMM estimation; this removes unobserved firm-specific effects, which could be correlated with regressors and generate biased results. Following Arellano and Bond (1991) and Bond and Cummins (2004), I treat uncertainty as an endogenous variable and choose the second and third lags for uncertainty, investment, cash holding, cash flow, their interactions with uncertainty, and year dummies as instruments. I use heteroskedasticity-consistent standard errors and test statistics. I report the Hansen overidentification test and Arellano and Bond's (1991) test for first order serial correlations. I find it useful to compare the estimates from dynamic panel estimations to the results from OLS and fixed effect regressions. As control variables, I use the cash flow and its lags, because the corporate finance literature shows that cash flow has a strong relationship with corporate investment (Fazzari et al. (1988), Blanchard et al. (1994), Lamont (1997)). I also include cash flow's interaction with uncertainty. Here I do not include average Q as a control variable because of problematic measurement issues as a measure of future investment opportunities. I include it later for some robustness checks.

## Baseline Regressions

Summary statistics are in Table .2. The firms' average investment rate is 0.25 and median is 0.18. The distribution of investment rate is quite right-skewed. The model's prediction is that a rise in uncertainty leads to a fall in investment. In this case, the magnitude of the fall should be compared with the investment distribution to determine its significance. Similarly, asset, capital stock and cash holding all have distributions that are right-skewed. Table .3 (left panel) shows the results of the regressions of investment-to-capital ratio ($\frac{I_t}{K_{t-1}}$, also called investment rate) on uncertainty ($\sigma_t$). The coefficients are significantly negative for OLS, fixed effect and dynamic panel regressions, and their magnitudes are similar. However, since

[12]The variables I choose are from Lamont (1997). These are the variables typically used for regression analysis on COMPUSTAT panel data.

Hansen's overidentification test indicates that my instruments are rejected, the estimates under GMM in the dynamic panel regressions should be used with caution. Nonetheless, my estimates are consistent with the theoretical predictions that high uncertainty lowers investment. The estimates indicate that a one standard deviation increase in volatility (uncertainty) leads to a drop of 0.04~0.05 in investment-to-capital ratio (a fall of 15%~20% in terms of its mean investment-to-capital ratio 0.25). The interaction term for cash flow and uncertainty has a significant negative relationship with the investment rate: Higher uncertainty makes firms less responsive to cash flow. The drop in investment-to-capital ratio is 0.049 in absolute terms. To measure the decrease in relative terms, I construct the growth rate of investment rate, dropping all investment that is negative at the beginning of the period (11% of all observations) and winsorize it at 1% and 99% to avoid outliers[13]. The same regressions are estimated on the growth rate of the investment rate. I find that a one standard deviation (0.038) increase in uncertainty leads to a 0.13 drop in OLS, a 0.16 drop in fixed effect regressions, and a 0.16 drop in dynamic panel regressions for relative terms.

## Regressions for Financially Constrained Firms

I use four criteria to obtain reasonable measures of financial frictions at the firm-level. The firm's asset, bond rating, dividend payout and Kaplan-Zingales index, albeit their imperfections, are widely adopted as proxies for financial constraints. I follow previous literature to use sample splitting based upon each measure to study the behavior of firms with different access to financial constraints. Following Bond et al. (2004) and Chen et al. (2010), each firm is marked in one subsample in *all* its sample years.

It is difficult for small firms to obtain external funds, big firms normally have easier access to various forms of financing, relationship banking, bond market, etc. I partition firms that differ in their asset size as proxies for a spectrum of credit conditions. The median asset is calculated for a firm in all its sample years and used to split my sample into 10 subsamples. Table .4 shows the summary statistics of those subsamples. The investment rates across different groups are quite similar. They are only slightly smaller for larger firms. The standard deviation of the investment rate, however, is higher for smaller firms. For uncertainty, there seems to be an decreasing pattern: smaller firms seem to subject to larger uncertainty. It is consistent with my understanding that smaller firms have more volatile growth prospects than larger firms. Cash flow is on average monotonically larger for bigger firms and its standard deviation higher for smaller firms. In addition, the asset holding is very right skewed.

From the OLS regressions (Table .5), for subgroups from the first eight deciles, the relationship between investment rate and uncertainty shows a negative sign and is statistically significant from zero. In contrast, the largest firms in the top quintile (top two deciles) of

[13] When investment is negative, the investment growth measure of a negative investment at time t-1 and positive increment from time t-1 to time t yields the same sign as in the case where the investment at time t-1 is positive and the increment is negative.

the sample do not respond significantly to uncertainty shocks. Larger firms tend to have a weaker response to uncertainty shocks, although the pattern is not monotonic. The R squared is smaller for smaller firms (less than ten percent for the first three deciles), and grows close to 40 percent for the largest decile. The interaction term of cash flow and uncertainty does not have a significant impact on investment rate. I also use the fixed effect model to purge the time-invariant effect for each firm. The results are quite similar to those from OLS. Larger firms appear to have a weaker relationship with the level of uncertainty, but the effect is not monotonic. The R squared is very similar to OLS estimates. The results from dynamic panel regressions are similar to those in fixed effect regressions. However, there is no significant uncertainty-investment relationship for the smallest size decile. The coefficient from this specification is larger than the other regressions. However, the Hansen J-test shows that the result is only instrument-proof for the top two quintiles. These finding are largely consistent with the prediction that investment from firms that are credit constrained tends to fall more due to uncertainty, while unconstrained firms are less responsive.

Borrowers use bond ratings to assess a firm's credit quality. According to Whited (1992), firms that use the corporate bond market are subject to more investor scrutiny, so they are more transparent and suffer less information asymmetries. By the same argument, firms without a bond rating typically find it hard to raise funds on the debt market, therefore they tend to have a more binding financial constraint. Table .6 shows us the summary statistics: first, there are many more firms without bond ratings than firms with bond ratings–the ratio is 12 to 1, meaning only one firm out of thirteen has a bond rating. Firms with bond ratings are more than ten times larger in assets. The investment rate is slightly larger for firms without bond ratings and the standard deviation for unrated firms is twice the number for rated firms. Uncertainty on firms without a rating is twice as large as the firms with bond ratings, both in terms of mean and standard deviation. Average cash flow is much smaller (negative) for unrated firms; the difference in mean is almost 100%. The standard deviation of cash flow on firms without rating is four folds the firms with bond ratings.

From the regression results of Table .7, coefficients on uncertainty are insignificant for firms without bond ratings. The coefficients for uncertainty of the bond rated firms, however, are negative and significant. The results are robust across OLS, fixed effect estimations and dynamic panel estimations. R squared of firms with bond ratings is 25 percent higher or more than firms without bond ratings. The magnitude of the drop in investment rate with respect to uncertainty is quite similar to the credit constrained firms defined in terms of size: a one standard deviation increase in uncertainty would result in over ten percent lower investment rate. Given the assumption that bond ratings are a valid measure of financial constraints, the results here is also consistent with my predictions.

Dividend payout has been an important measure used in corporate finance to identify financial constraints. Fazzari et al. (1988) argues that the retention practice provides a useful measure, because the cost disadvantage of external finance has a larger effect on firms that retain most of their earnings than on firms that distribute most of their earnings. Other work in corporate finance also shows that firms that are more constrained financially tend to pay out less dividends (Bolton et al. (2010b), Faulkender and Wang (2006))[14]. I make the assumption that the dividend payout ratio reveals the level of firms' financial condition and use Fazzari, Hubbard and Petersen's methodology to proxy for financial constraints. The sample is split into four subsamples using the amount of dividend distribution. Table .8 is the summary statistics across these subgroups. Firms in the first subgroup pay virtually no dividend and firms in the second subgroup pay very little. The investment rate is not very different, but the standard deviation across subgroups is large. Uncertainty is higher for firms that pay less dividends, but the standard deviation is similar. Firms that pay less dividends have a more negative cash flows and larger standard deviations than firms that pay more dividends.

From Table .9, regression outputs show that the top quartile dividend distributors do not respond to uncertainty significantly in either OLS, fixed effect or dynamic panel specifications. Under OLS and fixed effect estimations, uncertainty coefficients on investment rate for subgroups in the first three quartiles are negative and very significant. The R squared are lower for firms that pay no dividends and it is over twenty percent for firms in the top quartile. However, there is no significance on uncertainty for non-dividend-payers. Again, it is hard to be convinced because the Hansen test suggests the instruments are not valid. All the above results provide additional evidence that more financially constrained firms respond more negatively to an uncertainty shock.

The Kaplan-Zingales Index (Kaplan and Zingales (1997), Kaplan and Zingales (2000)) is another measure of financial friction, constructed based on a variables related to credit conditions. From a survey response of financial conditions, they estimate a relationship of a given set of variables to firms' financial state. This provides a score of financial constraint for every firm based upon various variables of interest as follows:

$$-1.001909\frac{CF_{it}}{A_{it-1}} + 3.139193LEV_{it} - 39.3678\frac{DIV_{it}}{A_{it-1}} - 1.314759\frac{C_{it}}{A_{ti-1}} + 0.2826389Q_{it}$$

where $\frac{CF_{it}}{A_{it-1}}$ is cash flow over lagged assets; $\frac{DIV_{it}}{A_{it-1}}$ is cash dividends over assets; $\frac{C_{it}}{A_{ti-1}}$ is cash balances over assets; $LEV_{it}$ is leverage; and $Q_{it}$ is the market value of equity (price times shares outstanding from CRSP) plus assets minus the book value of equity all over assets. Following Baker et al. (2003), I winsorize every variable at 1% and 99%. The Kaplan-Zingales index has been used extensively as a measure of financial constraints (Lamont et al. (2001), Hennessy et al. (2007), Baker et al. (2003), for example)[15].

Summary statistics are in Table .10. There appears to be an upper trend across deciles for investment. The less financially constrained from the left, measured by KZ index, have

[14] However, I am well aware of the debate on whether the dividend payout ratio provides a good measure of financial constraint (Kaplan and Zingales (1997), Fazzari et al. (2000), Kaplan and Zingales (2000)). This paper does not provide additional insight on whether it is a good measure of financial constraints.

[15] However, Almeida et al. (2004), Whited and Wu (2006) and Hadlock and Pierce (2010) question the validity of Kaplan-Zingales index as a measure of financial constraints.

a lower average investment rate and lower volatility of investment rate. The mean and standard deviation are quite close. Cash flow is lower for financially constrained firms in the upper deciles and its corresponding standard deviations higher. Financially unconstrained firms are larger in terms of size, especially for the bottom decile (0-10%).

From Table .11, I observe that there is only one coefficient on uncertainty that is not significant–that is the one for the most financially unconstrained firms measured by KZ index in the first decile. Coefficients on the second and third deciles have significance at 5% while the rest are significant at 1%. Although the result is not very impressive, it is suggestive of my story that the investment rate from unconstrained firms, compared to the investment rate from constrained counterparts, are less responsive to an uncertainty shock. Table .11 also presents a result that is in general consistent, although the coefficient on the second decile is quite significant and its magnitude surpasses that of the third decile. From the dynamic panel regressions, the top forty percent of the firms' investment behaviors are significantly affected by uncertainty. The magnitudes of an investment adjustment are different across firms.

However, Leahy and Whited (1996) find insignificant investment response in a regression of investment rates. From my results, regression coefficients of unconstrained firms tend to be insignificant and those of constrained firms are significant and negative. Therefore, based on this reasoning, the overall regression might show a significant or insignificant coefficient depending on what kind of firms dominate.

## Robustness

Because this paper studies the second-moment effect, it is important to control for the first-order effect, which relates to the mean profitability. Because I measure the second-moment shock using the stock return volatility, I try both the mean annual stock return to control for the first-order effect. Average Q, as a measure of Tobin's Q, is also included to account for the mean future profitability. Leahy and Whited (1996) find that the impact of uncertainty disappears after they control for the average Q and thus argue that uncertainty affects investment only through Q. However, here Q does not affect the main results.

Firm size is an important determinant of financial frictions. However, it may also affect other factors, such as productivity and industry-level effects. I include capital stock in every regression and its coefficient appears to be significant in most regressions. The main findings remain robust. In the regression in my web appendix, I include average Q, stock returns, capital stock and their interaction with uncertainty as additional control variables. Similar results are reported

This section also checks the robustness for various measures of uncertainty. In addition to the baseline measure (volatility of daily stock returns), I construct four other measures: high uncertainty, normalized uncertainty, monthly uncertainty and residual uncertainty. High uncertainty is a zero-one measure that returns one if the firm's measured uncertainty surpass that the firm's sample mean by at least one standard deviation. The normalized uncertainty normalizes the stock-based uncertainty by the square-root of the debt-to-equity ratio. Previous papers use this calculation to control for the fact that the more highly-leveraged firms have larger risks. Monthly uncertainty based on the monthly stock returns is a less noisy alternative measure. I also use the difference between daily individual stock returns and the market returns to substitute for the daily stock returns, and compute its volatility for the residual uncertainty measure. Such constructions reduce the effect of aggregate shocks on the uncertainty measure. Regression analysis using all those measures yield qualitatively similar results (see web appendix for details).

The dependent variable is the investment-to-capital ratio. I construct the the replacement value of capital using the perpetual inventory method in Salinger and Summers (1983). However, the results will be affected if the constructed measure of capital deviates from its true value. To this end, I use the reported book value of the company's gross property, plant and equipment as an alternative measure of the capital stock. Its mean is larger than the replacement value of capital hence the investment-to-capital ratios are smaller on average. Estimations show qualitatively similar results with smaller magnitudes.

## High Uncertainty

The regression analysis provides results of contemporaneous relationship between uncertainty and investment. A related question is how investment changes over time after a rise in the level of uncertainty? To answer this question, I explore graphically the relationship between firms' uncertainty and investment dynamics. I first need to construct a shock of uncertainty at firm-level to reconcile my results with Bloom's (2009) estimated investment dynamics after an uncertainty shock. To this end, I define a firm in a high uncertainty state in a given year as a firm with measured uncertainty at least one standard deviation higher than its mean uncertainty over all the company's sample years. To visualize high uncertainty over time, for each year, I compute the fraction of firms that are in the state of high uncertainty. (See Figure .7).

Interestingly, under this measure of high uncertainty, the current credit crunch from 2008 brings the highest aggregate uncertainty in the past 40 years: Over 60 percent of the firms are in a high uncertainty state in years 2008 and 2009. The second largest uncertainty shoot-up is around the year 1999-2001, in which the LTCM bankruptcy, tech-bubble burst and September 11 attacks happened in three consecutive years. High uncertainty is also observed in the OPEC oil crisis (1974), Black Monday (1987) and the first Gulf War (1991). This plot is loosely comparable to Figure 1 in Bloom (2009), which shows the monthly implied volatility for aggregate stock market returns. Given those uncertainty shocks, I am particularly interested in firms' investment and financing behaviors in episodes of high uncertainty. I try to summarize firms' behavior under uncertainty shocks and give policy guidance, especially in the midst of the current credit crunch–a period with the highest uncertainty in the past 40 years. This result concurs with Bloom's (2009) finding using implied market volatility over time.

## The Dynamic Response to Uncertainty

Previous section studies a cross-sectional response while in this section, I use my definition of high uncertainty to see the dynamics of firms' behavior after an increase in uncertainty. I could follow Leary and Roberts (2005) to split my sample into two portfolios–firms with high uncertainty during the year and those without – and track the mean investment for uncertainty firms and other firms. However, serial correlation of high uncertainty and its first lag is 0.15, and the rest of lags are negative and close to zero. This imposes a serious problem with this methodology, making the pre- and post-uncertainty-shock investment fall as well. Therefore, I construct a simple model to account for serial correlation in uncertainty. The choice in this paper is a reduced-form specification of an autoregressive distributed lag (ADL) model with an AR(1) structure on uncertainty:

$$\begin{aligned}\left(\frac{I}{K}\right)_{it} &= \alpha\left(\frac{I}{K}\right)_{it-1} + \beta X_{it} + \sum_{j=0}^{k}\gamma_j \sigma_{it-j} + u_{it}\\ \sigma_{it} &= \phi\sigma_{it-1} + \epsilon_{it}\end{aligned}$$

Similar to the models in previous regression analyses, $\left(\frac{I}{K}\right)_{it}$ is the investment rate, $X_{it}$ is the vector of control variables, and $\sigma_{it}$ is the uncertainty measure. Three lags in the uncertainty lag specification are chosen to show the time dynamics and ensure that few data points are dropped due to length and consistency of the data. For simplicity, I assume the error terms from the two equations, $u_{it}$ and $\epsilon_{it}$ are uncorrelated. An impulse response and its corresponding 95% confidence band are constructed based on the panel coefficient estimates (See Appendix D for details).

Figure .8 shows the uncertainty impulse response for all firms. The horizontal axis indicates the year before and after high uncertainty with zero the year of impact. I see a 3%~4% contemporaneous sharp decline in investment rate when high uncertainty arrives. And after two years it reverts back to its original level and overshoots after. And the changes at the year of impact and the year after are significant in terms of the confidence band. This is consistent with Bloom's (2009) finding for aggregate time series.

As a first pass to study the impact of financial frictions, I decompose my sample to five subgroups based on size (capital). In the corporate finance literature, size is found to be an important determinant of financial frictions. For example, Fazzari et al. (1988) found evidence that liquidity constraints tend to be systematically more binding for smaller firms. In a seminar paper on financial frictions, Petersen and Rajan (1994) observe that small and young firms are most likely to face more information asymmetry in lending relationship and therefore more likely to be credit rationed. Bernanke et al. (1999) explicitly use firm size (capital) as a collateral for external financing and suggest that bigger firms are able to obtain more financing. Firm size, albeit an imperfect measure, is commonly used for empirical studies of corporate financing constraints[16]. My results for different size quintiles in Figure .9 show that, for the firms in the top quintile (top 20% percentile), the drop of their investment in response to high uncertainty is merely 0.01; the drop is not statistically significant and it moves back quickly after one year. The firms in the bottom quintile (bottom 20 percentile), however, have experienced a large and statistically significant fall in investment rate (close to 0.05) and revert back slowly to the original level after three years.

Whited (1992) splits the sample into firms with bond rating and firms without bond ratings to study liquidity constraints and firm investment. She argues that firms with bond ratings tend to have less information asymmetry, so it would be easier for them to obtain debt financing; in this sense, they are less financially constrained. Following her criteria, I divide my sample based on whether a firm has a bond rating or not. From Figure .10, there are more striking results: firms' investment with bond rating shows virtually no evidence of decrease and the coefficients are insignificant from zero after impact. There is a significant drop in investment from firms with no bond rating.

In an influential paper, Fazzari et al. (1988) categorize firms according to dividend payouts to study financing constraints and corporate investment. I do the same exercises in terms of the amount of dividend paid in Figure .11. For firms that pay a lot of dividends, the decline in investment rate is minimal and quickly reverts back. The fall in these two categories are insignificant from zero. Firms that do not pay dividends (<25%) or pay very little (25%-50%) experience very large drop.

All the results above are consistent with the predictions that investment behavior by financially-constrained firms is very different from that of financially unconstrained firms. Imposing a simple structure on the dynamics of investment and uncertainty allows me to see the dynamics of how investment behaves in response to an uncertainty shock and how responses are different across firms with heterogeneous financial constraints. It is important to notice this effect because it allows for further empirical investigations. The downside of such a simple specification is that it might be too restrictive for my analysis. In the next section, I use more regressions and more proxies of financial frictions to test my predictions.

## 1.5 Conclusion and Policy Implications

In the crisis starting in the fourth quarter of 2007, there has been a dramatic increase in uncertainty, in magnitudes similar to the Great Depression. In such a period of high uncertainty, the usual policy instruments might not be as effective as in normal times. In particular, Bloom (2009) argues that high uncertainty induces more wait-and-see in investment and hiring for firms, so that stimulus policies in high-uncertainty episodes may be less effective. From my study, I look more closely into the uncertainty-investment relationship

[16] An incomplete list is Devereux and Schiantarelli (1990) for UK firms, Athey and Laumas (1994) for indian firms, Gilchrist and Himmelberg (1995) for US data, Kadapakkam et al. (1998) for firms from six OECD countries, etc.

in historical firm-level data. The results are partially consistent with Bloom's (2009) argument. Interestingly, I find that the uncertainty-investment relationship is heterogeneous among firms with different levels of access to the credit market. For firms that have easier access to the credit market, the uncertainty-investment relationship is much lower.

There are two important policy implications of my findings. First, a stimulus policy affects firms differently. Firms without good financing opportunities are more affected in high-uncertainty episodes and, hence, less responsive to stimulus[17]. Thus, policies could be customized for firms with and without good credit conditions. To induce a quick responses from firms with high costs of accessing the credit market, policy makers would need to grant more access to liquidity.

The second implication is related to heterogeneity across time. Firms face different credit conditions over time. Borrowing in 2008 is very difficult, while just two years earlier, firms enjoyed very good credit conditions. The credit crunch amplifies the impact of uncertainty on firm investment and hiring. Firms are even less willing to respond to the stimulus. Either improving firms' credit condition or lowering the level of uncertainty could help induce the firm to spend on capital or hiring.

In conclusion, this paper studies the relationship among uncertainty, financial constraints, and investment. Investment from firms with different financial frictions responds significantly differently to uncertainty. This finding is consistent with a model that incorporates non-convex adjustment costs, time-varying uncertainty and financial frictions.

Theoretically, this paper is among the first models to study the interaction between all three variables. It contributes to macroeconomic production models by incorporating the firms' external financing and saving along with time-varying uncertainty. My contribution to the corporate finance literature is modeling the second-order volatility effect in a model with investment and financing decisions. On the empirical side, this is the first paper to study the uncertainty-investment relationship across different firm groups, to the best of my knowledge. This paper contributes to a long literature studying the relationship of firm investment and financing conditions (Fazzari et al. (1988), Kaplan and Zingales (1997) etc). I find a new systematic way in which financing conditions affect firm investment. This empirical finding also adds to the list of studies on the uncertainty-investment relationship (Leahy and Whited (1996), Baum et al. (2008), Bloom (2009)) .

Important policy implications can be derived from this paper. My model suggests that an effective stimulus policy for firms would take into account the differences in firms' credit conditions. Smaller and more credit constrained firms will be less responsive to policy in an episode of high uncertainty. Therefore, policies targeted to effectively stimulate those firms must also address their liquidity concerns.

[17] The stimulus plan could be either a demand side stimulus, such as a plan stimulating consumer spending, or a firm stimulus, such as tax benefits.

# APPENDIX

## Numerical Solution

### Algorithm

I use value function iteration (Judd (1998), Adda and Cooper (2003)) on the state variables $(K, P, A, \sigma)$ to achieve convergence by the following algorithm:

Set grid points for each of the four states $(K, P, A, \sigma)$. In this study I use $50 \times 50 \times 50 \times 2 = 250,000$ points for most of my results. Finer grids up to $100 \times 100 \times 100 \times 2 = 2,000,000$ points are also tried for some specifications. The results are similar throughout. Grids of $A$ and $\sigma$ are defined from a quadrature I constructed in the next section. I also use a variant of quadrature from Tauchen (1986) that takes into account the changing volatility and uses a set of grids that cluster more around the inaction region, an effort to capture the change in the inaction zone more accurately. The quality of quadrature is important because the time-varying uncertainty strongly influences expectations. To ensure that $K$ stays on the grid all the time, and especially in the case for inaction where investment is null and the next period's $K$ becomes $(1-\delta)K$, I specify grids for $K$ as $\left[(1-\delta)^j \bar{K}, ..., (1-\delta)\bar{K}, \bar{K}\right]$. Because I define everything on the grids and their movement is restricted to the specified grids, I do not do interpolation. This is an advantage and produces more robust results. For the productivity shock, because the logarithm of $A$ has an AR(1) structure, I have to account for the Jensen correction term when taking the exponential of it. I subtract $\sigma^2/2$ from the drift term of the AR(1) process.[18] I define value function on the grid and iterate value function using the Bellman equation. I start with an initial value for the value function that has the same value for every state. It takes on average 3 hours to solve the dynamic programming program, although the running time varies with parameters.

### Construction of Quadrature

In standard models with firm investment, firms make investment choices based upon their forecast of future profitability $A$. Because this model incorporates time-varying uncertainty, the expectation of the uncertainty change is also a deterministic factor for firms' investment behavior. Therefore, the numerical method must capture the expectation well. I construct a new quadrature with time-varying volatility based on Adda and Cooper (2003). Denote the logarithm of technology shock $A$ as $x$ and $x$ follows an AR(1) process with switching

[18] In the appendix of Bloom (2009), he also address this problem by "...uncertainty effect on the drift rate is second order compared to the real-options effect, so the simulations are virtually unchanged if this correction is omitted."

standard deviations:

$$
\begin{aligned}
x' &= \mu + \rho x + v, \quad v \sim N(0,\sigma^2) \\
\sigma &\in \{\sigma_L, \sigma_H\}, \quad where \quad Pr(\sigma' = \sigma_j | \sigma = \sigma_k) = p_{k,j} \\
\mu &\in \{\mu_L, \mu_H\}, \quad with \quad same \quad transition \quad probabilities
\end{aligned}
$$

The reason I change $\mu$ when $\sigma$ changes is because I need to account for the Jensen's correction term in the mean if I want to control for the same level of change in $A$. The trick is to define a set of grids and transition probabilities that works for both $\sigma_L$ and $\sigma_H$. First define

$$
\begin{aligned}
\sigma &= \left(\sigma_x^L \sigma_x^H\right)^{\frac{1}{2}} \\
where \quad \sigma_x^L &= \frac{\sigma_L}{\sqrt{1-\rho^2}} \quad and \quad \sigma_x^H = \frac{\sigma_H}{\sqrt{1-\rho^2}} \\
\mu &= \frac{\mu_x^L + \mu_x^H}{2} \\
where \quad \mu_x^L &= \frac{\mu_L}{1-\rho} \quad and \quad \mu_x^H = \frac{\mu_H}{1-\rho}
\end{aligned}
$$

Given the normality assumption, I define the cutoff points $\{x^i\}_{i=1}^{N+1}$ as follows:

$$
\Phi\left(\frac{x^{i+1}-\mu}{\sigma}\right) - \Phi\left(\frac{x^i-\mu}{\sigma}\right) = \frac{1}{N}, \quad i = 1, ..., N
$$

where $\Phi(\cdot)$ is the normal cdf and solve it recursively,

$$
\begin{aligned}
x^i &= \sigma \Phi^{-1}\left(\frac{i-1}{N}\right) + \mu, \quad i = 1, ..., N \\
&= \left(\sigma_x^L \sigma_x^H\right)^{\frac{1}{2}} \Phi^{-1}\left(\frac{i-1}{N}\right) + \frac{\mu_x^L + \mu_x^H}{2}, \quad i = 1, ..., N
\end{aligned}
$$

Then an important formula, which I am going to use extensively later, becomes the following:

$$\Phi\left(\frac{x^{i+1}-\mu_x^L}{\sigma_x^L}\right)-\Phi\left(\frac{x^{i}-\mu_x^L}{\sigma_x^L}\right)=\Phi\left(\left(\frac{\sigma_x^H}{\sigma_x^L}\right)^{\frac{1}{2}}\Phi^{-1}\left(\frac{i}{N}\right)+\frac{\mu_x^H-\mu_x^L}{2\sigma_x^L}\right)$$
$$-\Phi\left(\left(\frac{\sigma_x^H}{\sigma_x^L}\right)^{\frac{1}{2}}\Phi^{-1}\left(\frac{i-1}{N}\right)+\frac{\mu_x^H-\mu_x^L}{2\sigma_x^L}\right)$$
$$\Phi\left(\frac{x^{i+1}-\mu_x^H}{\sigma_x^H}\right)-\Phi\left(\frac{x^{i}-\mu_x^H}{\sigma_x^H}\right)=\Phi\left(\left(\frac{\sigma_x^L}{\sigma_x^H}\right)^{\frac{1}{2}}\Phi^{-1}\left(\frac{i}{N}\right)-\frac{\mu_x^H-\mu_x^L}{2\sigma_x^H}\right)$$
$$-\Phi\left(\left(\frac{\sigma_x^L}{\sigma_x^H}\right)^{\frac{1}{2}}\Phi^{-1}\left(\frac{i-1}{N}\right)-\frac{\mu_x^H-\mu_x^L}{2\sigma_x^H}\right)$$

Now for each interval, I define a value associated with it, $z^i$:

$$z^i = E\left(x_t|x_t\in\left[x^i,x^{i+1}\right]\right)$$
$$=\frac{p_{LH}}{p_{LH}+p_{HL}}\left\{\sigma_x^H\frac{\phi\left(\frac{x^i-\mu_x^H}{\sigma_x^H}\right)-\phi\left(\frac{x^{i+1}-\mu_x^H}{\sigma_x^H}\right)}{\Phi\left(\frac{x^{i+1}-\mu_x^H}{\sigma_x^H}\right)-\Phi\left(\frac{x^{i}-\mu_x^H}{\sigma_x^H}\right)}+\mu_x^H\right\}$$
$$+\frac{p_{HL}}{p_{LH}+p_{HL}}\left\{\sigma_x^L\frac{\phi\left(\frac{x^i-\mu_x^L}{\sigma_x^L}\right)-\phi\left(\frac{x^{i+1}-\mu_x^L}{\sigma_x^L}\right)}{\Phi\left(\frac{x^{i+1}-\mu_x^L}{\sigma_x^L}\right)-\Phi\left(\frac{x^{i}-\mu_x^L}{\sigma_x^L}\right)}+\mu_x^L\right\}$$
$$=\frac{p_{LH}}{p_{LH}+p_{HL}}\left\{\sigma_x^H\frac{\phi\left(\frac{x^i-\mu_x^H}{\sigma_x^H}\right)-\phi\left(\frac{x^{i+1}-\mu_x^H}{\sigma_x^H}\right)}{\Phi\left(\left(\frac{\sigma_x^H}{\sigma_x^L}\right)^{\frac{1}{2}}\Phi^{-1}\left(\frac{i}{N}\right)+\frac{\mu_x^H-\mu_x^L}{2\sigma_x^L}\right)-\Phi\left(\left(\frac{\sigma_x^H}{\sigma_x^L}\right)^{\frac{1}{2}}\Phi^{-1}\left(\frac{i-1}{N}\right)+\frac{\mu_x^H-\mu_x^L}{2\sigma_x^L}\right)}+\mu_x^H\right\}$$
$$+\frac{p_{HL}}{p_{LH}+p_{HL}}\left\{\sigma_x^L\frac{\phi\left(\frac{x^i-\mu_x^L}{\sigma_x^L}\right)-\phi\left(\frac{x^{i+1}-\mu_x^L}{\sigma_x^L}\right)}{\Phi\left(\left(\frac{\sigma_x^L}{\sigma_x^H}\right)^{\frac{1}{2}}\Phi^{-1}\left(\frac{i}{N}\right)-\frac{\mu_x^H-\mu_x^L}{2\sigma_x^H}\right)-\Phi\left(\left(\frac{\sigma_x^L}{\sigma_x^H}\right)^{\frac{1}{2}}\Phi^{-1}\left(\frac{i-1}{N}\right)-\frac{\mu_x^H-\mu_x^L}{2\sigma_x^H}\right)}+\mu_x^L\right\}$$

Notice that for the third equation I replace expression that has $A^i$ grids and normal in the denominators with an expression that does not have $A^i$ grids in it. This greatly improves accuracy. And lastly I calculate the transition probabilities. Now because I have two uncertainty states, the transition probabilities from grid $i$ to grid $j$ are based on $\sigma$:

$$\begin{aligned}
\pi_{i,j}(\sigma_H) &= Prob\left(x_t \in \left[x^j, x^{j+1}\right] | x_{t-1} \in \left[x^i, x^{i+1}\right], \sigma_H\right) \\
&= \frac{\int_{x^i}^{x^{i+1}} e^{-\frac{(\epsilon-\mu_x^H)^2}{2\sigma_x^H}} \left\{\Phi\left(\frac{x^{j+1}-\mu_H-\rho\epsilon}{\sigma_H}\right) - \Phi\left(\frac{x^j-\mu_H-\rho\epsilon}{\sigma_H}\right)\right\} d\epsilon}{\sqrt{2\pi\sigma_x^{H2}} \cdot \left\{\Phi\left(\frac{x^{i+1}-\mu_x^H}{\sigma_x^H}\right) - \Phi\left(\frac{x^i-\mu_x^H}{\sigma_x^H}\right)\right\}} \\
&= \frac{\int_{x^i}^{x^{i+1}} e^{-\frac{(\epsilon-\mu_x^H)^2}{2\sigma_x^H}} \left\{\Phi\left(\frac{x^{j+1}-\mu_H-\rho\epsilon}{\sigma_H}\right) - \Phi\left(\frac{x^j-\mu_H-\rho\epsilon}{\sigma_H}\right)\right\} d\epsilon}{\sqrt{2\pi\sigma_x^{H2}} \cdot \left\{\Phi\left(\left(\frac{\sigma_x^H}{\sigma_x^L}\right)^{\frac{1}{2}} \Phi^{-1}\left(\frac{i}{N}\right) + \frac{\mu_x^H-\mu_x^L}{2\sigma_x^L}\right) - \Phi\left(\left(\frac{\sigma_x^H}{\sigma_x^L}\right)^{\frac{1}{2}} \Phi^{-1}\left(\frac{i-1}{N}\right) + \frac{\mu_x^H-\mu_x^L}{2\sigma_x^L}\right)\right\}}
\end{aligned}$$

and

$$\begin{aligned}
\pi_{i,j}(\sigma_L) &= Prob\left(A_t \in \left[A^j, A^{j+1}\right] | A_{t-1} \in \left[A^i, A^{i+1}\right], \sigma_L\right) \\
&= \frac{\int_{x^i}^{x^{i+1}} e^{-\frac{(\epsilon-\mu_x^L)^2}{2\sigma_x^L}} \left\{\Phi\left(\frac{x^{j+1}-\mu_L-\rho\epsilon}{\sigma_L}\right) - \Phi\left(\frac{x^j-\mu_L-\rho\epsilon}{\sigma_L}\right)\right\} d\epsilon}{\sqrt{2\pi\sigma_x^{L2}} \cdot \left\{\Phi\left(\frac{x^{i+1}-\mu_x^L}{\sigma_x^L}\right) - \Phi\left(\frac{x^i-\mu_x^L}{\sigma_x^L}\right)\right\}} \\
&= \frac{\int_{x^i}^{x^{i+1}} e^{-\frac{(\epsilon-\mu_x^L)^2}{2\sigma_x^L}} \left\{\Phi\left(\frac{x^{j+1}-\mu_L-\rho\epsilon}{\sigma_L}\right) - \Phi\left(\frac{x^j-\mu_L-\rho\epsilon}{\sigma_L}\right)\right\} d\epsilon}{\sqrt{2\pi\sigma_x^{L2}} \cdot \left\{\Phi\left(\left(\frac{\sigma_x^L}{\sigma_x^H}\right)^{\frac{1}{2}} \Phi^{-1}\left(\frac{i}{N}\right) - \frac{\mu_x^H-\mu_x^L}{2\sigma_x^H}\right) - \Phi\left(\left(\frac{\sigma_x^L}{\sigma_x^H}\right)^{\frac{1}{2}} \Phi^{-1}\left(\frac{i-1}{N}\right) - \frac{\mu_x^H-\mu_x^L}{2\sigma_x^H}\right)\right\}}
\end{aligned}$$

Thus the complete transition probabilities are

$$\begin{aligned}
\pi_{ij,LH} &= p_{LH} \cdot \pi_{i,j}(\sigma_H), \quad \pi_{ij,LL} = p_{LL} \cdot \pi_{i,j}(\sigma_L) \\
\pi_{ij,HL} &= p_{HL} \cdot \pi_{i,j}(\sigma_L), \quad \pi_{ij,HH} = p_{HH} \cdot \pi_{i,j}(\sigma_H)
\end{aligned}$$

The uncertainty state here is binary. But my methodology can be extended to uncertainty state with multiple grids.

# Investment Critical Value, Uncertainty and Adjustment Cost

This section studies the question how adjustment cost affects the relationship between investment critical value and uncertainty, under a simple continuous-time framework. In a simple real-option framework, firms with higher adjustment cost will have larger investment inaction region in response to high uncertainty shocks. The derivation closely follows Dixit and Pindyck (1994) Chapter 5. I consider the following problem: Firms decide when to invest with a fixed cost $C$ in a project of value $V$, which follows a geometric Brownian motion:

$$dV = \mu V dt + \sigma V dW \tag{.16}$$

Denote the present value of the project as $F(V)$:

$$F(V) = \max E\left\{e^{-\rho T}\left(V_T - C\right)\right\} \tag{.17}$$

$T$ is the (unknown) time the firm decides to invest and $\rho$is the discount rate. Because there is no cash from the project until it is invested, the Bellman equation becomes

$$\rho F dt = E(dF) \tag{.18}$$

Applying Ito's Lemma, I have

$$\frac{1}{2}\sigma^2 V^2 F''(V) + \mu V F'(V) - \rho F = 0 \tag{.19}$$

subject to the following boundary conditions

$$F(0) = 0 \tag{.20}$$
$$F(V^*) = V^* - C \tag{.21}$$
$$F'(V^*) = 1 \tag{.22}$$

where $V^*$denotes the critical value of investment, or equivalently the upper-bound for investment inaction. And I use $C$ to denote the cost associated with investment in this project. Firm investment when the project value $V$ exceeds $V^*$. To formalize the argument $V^*$satisfies $V^* - F(V^*) = C$.

I guess the solution takes the simple form:

$$F(V) = AV^{\beta} \tag{.23}$$

By using all above equations, I have

$$V^* = \frac{\beta}{\beta - 1} C \tag{.24}$$

where $\beta$ is the positive root to the quadratic equation below:

$$\frac{1}{2}\sigma^2 \beta(\beta - 1) + \mu\beta - \rho = 0 \tag{.25}$$

So I have a relationship between the investment critical value, $V^*$, level of uncertainty $\sigma^2$ and the non-convex cost associated with investment $C$. In this paper I am interested in how the investment-critical-value-uncertainty relationship changes as I vary the capital adjustment cost $C$. This is a second derivative of $V^*$ with respect to both $\sigma^2$ and $C$: $\frac{\partial^2 V^*}{\partial\sigma\partial C}$. It is obvious from the formula for $V^*$ that $\frac{\partial V^*}{\partial C} = \frac{\beta}{1-\beta}$. And if I define the quadratic equation of $\beta$ as $Q$, then a total differentiation gives us

$$\frac{\partial Q}{\partial \beta} \cdot \frac{\partial \beta}{\partial \sigma} + \frac{\partial Q}{\partial \sigma} = 0 \tag{.26}$$

Because $\frac{\partial Q}{\partial \beta}$ and $\frac{\partial Q}{\partial \sigma}$ are both greater than zero, I have

$$\frac{\partial \beta}{\partial \sigma} < 0 \tag{.27}$$

Therefore

$$\frac{\partial^2 V^*}{\partial \sigma \partial C} = \partial \left[ \frac{\beta}{\beta - 1} \right] / \partial \sigma = -\frac{\partial \beta / \partial \sigma}{(\beta - 1)^2} > 0 \tag{.28}$$

This means that in this simple real-option model, the expansion of inaction region in response to high uncertainty, captured by $\frac{\partial V^*}{\partial \sigma}$, will be larger for firms with higher capital adjustment cost $C$.

# Variable Construction

1. Uncertainty: For each firm-year, I calculate the standard deviation of stock returns over that fiscal year of a firm and match the financial statement information with the standard deviation of daily stock return data. For any uncertainty observation that is great than five, I trim it to five. This construction of uncertainty is used by Bloom et al. (2007). However, unlike Leahy and Whited (1996) and Bond and Cummins (2004), I did not scale it by the debt-to-equity ratio in the baseline uncertainty calculation, because this normalization is rather arbitrary. I do not want to complicate the measure by adding company's leverage, because the investment is affected by leverage ratio. To illustrate this point I provide some statistics to justify this concern. The measure they use is $\sigma \cdot \sqrt{\frac{equity}{debt}}$. Calculations show that $\sigma$ has a mean 0.038 and standard deviation 0.022 while the mean and standard deviation for $\sqrt{\frac{equity}{debt}}$ is more than $100\times$ larger in comparison: 5.42 and 15.76. If it is normalized, the variation of uncertainty is partly driven by the debt-to-equity, which makes us question the validity of this uncertainty measure. Since the average leverage ratio is about ten percentage, my measure of uncertainty is only one tenth of the value in Leahy and Whited (1996)[19] and Bond and Cummins (2004). Nevertheless, Bond and Cummins (2004) show results that are similar for the magnitude of investment change in response to a one standard deviation

[19] They calculate variances rather than standard deviations.

increase in uncertainty. Instead of using the market equity, the book equity is used to normalize uncertainty for robustness.

2. Replacement Value of Capital: Since the capital stock[20] are recorded in historic value, it is necessary to correct for the bias by estimating the firms' replacement value capital stock. I follow the literature using COMPUSTAT data to construct this estimate use the perpetual inventory method used in Salinger and Summers (1983). Several assumptions are required to construct the series and are discussed in more detail in the Salinger and Summers paper. First, the equipment's fixed capital has a common useful life ($L$). Second, because COMPUSTAT does not report the method that firms use to depreciate their capital stock in any detail, all firms are assumed to use straight line methods for book depreciation. Third, actual depreciation is exponential with rate $2/L$, equivalent to double-declining digits depreciation. Fourth, all investments are made at the beginning of the year, and all depreciation is taken at the end of the year. Last, the value of reported gross property, plant and equipment ($PPE$) in the initial year that the firm appears in the sample is equal to its replacement value, thus functioning as a seed value for the Salinger and Summers algorithm. The formula $L_t = (PPE_{t-1}+I_t)/DEP_t$ provides an estimate of the useful lifetime of fixed capital. $PPE$ represents the book value of gross property, plant and equipment, $I$ is capital expenditures, and $DEP$ is book depreciation. Instead of allowing the estimated useful life to fluctuate from year to year, I use each the average of each firms $L$. In addition, if reported depreciation is small in any given year, $L$ becomes implausibly large. I place an upper bound of forty years and a lower bound of three years on $L$. The Salinger-Summers algorithm uses a method similar to perpetual inventory methods to create the replacement cost estimate of $K$. The actual formula is: $K_{it} = (K_{it-1}\frac{P_t}{P_{t-1}} + I_{it})(1 - 2/L_{it})$.

# ADL Impulse Response

The Autoregressive Distributed Lag (ADL) to investigate for the investment-uncertainty relationship is the following:

$$\left(\frac{I}{K}\right)_{it} = \alpha \left(\frac{I}{K}\right)_{it-1} + \beta X_{it} + \sum_{j=0}^{k} \gamma_j \sigma_{it-j} + u_{it} \tag{.29}$$

$$\sigma_{it} = \phi\sigma_{it-1} + \epsilon_{it} \tag{.30}$$

In this construction, $\left(\frac{I}{K}\right)_{it}$ is the investment rate, $X_{it}$ is the vector of control variables and $\sigma_{it}$ is the uncertainty shocks. Given a one unit $\epsilon_{it}$ shock, the contemporaneous impact

[20] PPE: Property, plant and equipment

on investment rate

$$\left(\frac{I}{K}\right)_{it} = \gamma_0 \tag{.31}$$

Investment rate for the first year

$$\left(\frac{I}{K}\right)_{it+1} = (\alpha + \phi)\gamma_0 + \gamma_1 \tag{.32}$$

Investment rate for the second year

$$\begin{aligned}\left(\frac{I}{K}\right)_{it+2} &= \alpha\left(\frac{I}{K}\right)_{it+1} + \gamma_0\phi^2 + \gamma_1\phi + \gamma_2 \\ &= \alpha\left((\alpha+\phi)\gamma_0 + \gamma_1\right) + \gamma_0\phi^2 + \gamma_1\phi + \gamma_2 \end{aligned} \tag{.33}$$

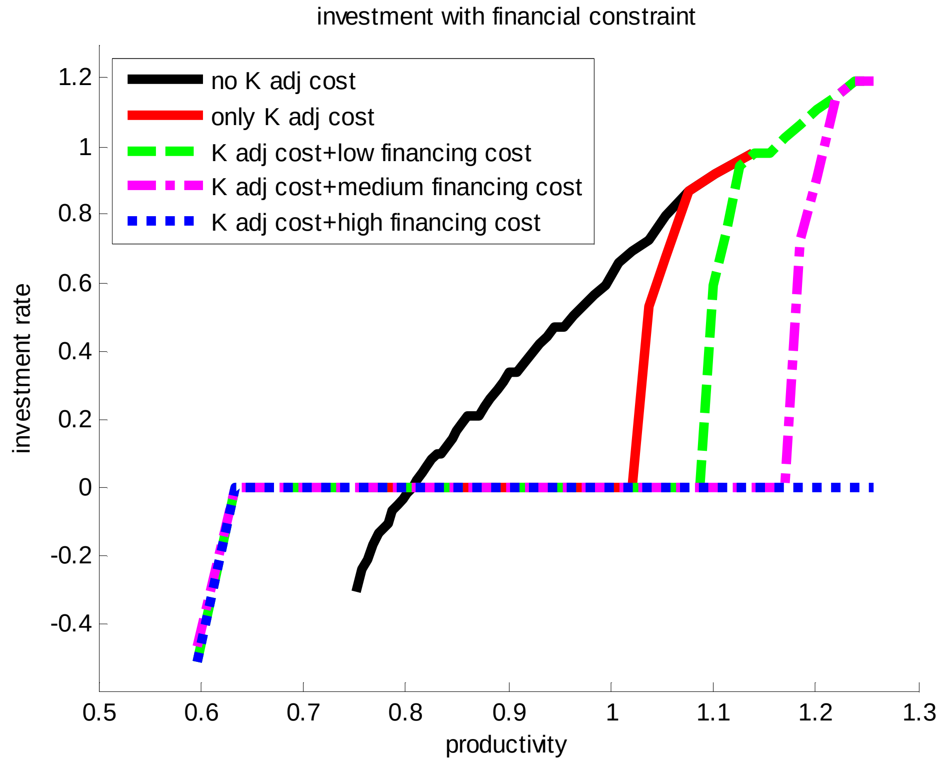
Investment rate for the third year

$$\begin{aligned}\left(\frac{I}{K}\right)_{it+3} &= \alpha\left(\frac{I}{K}\right)_{it+2} + \gamma_0\phi^3 + \gamma_1\phi^2 + \gamma_2\phi + \gamma_3 \\ &= \alpha\Big(\alpha\left((\alpha+\phi)\gamma_0 + \gamma_1\right) + \gamma_0\phi^2 + \gamma_1\phi + \gamma_2\Big) + \gamma_0\phi^3 + \gamma_1\phi^2 + \gamma_2\phi + \gamma_3 \end{aligned} \tag{.34}$$

The number of lags for uncertainty shocks $k = 3$. Equation (.29) and equation (.30) are estimated separately. To justify this estimation, I show that the residuals term from equation (.29) and equation (.30) have a correlation of zero.

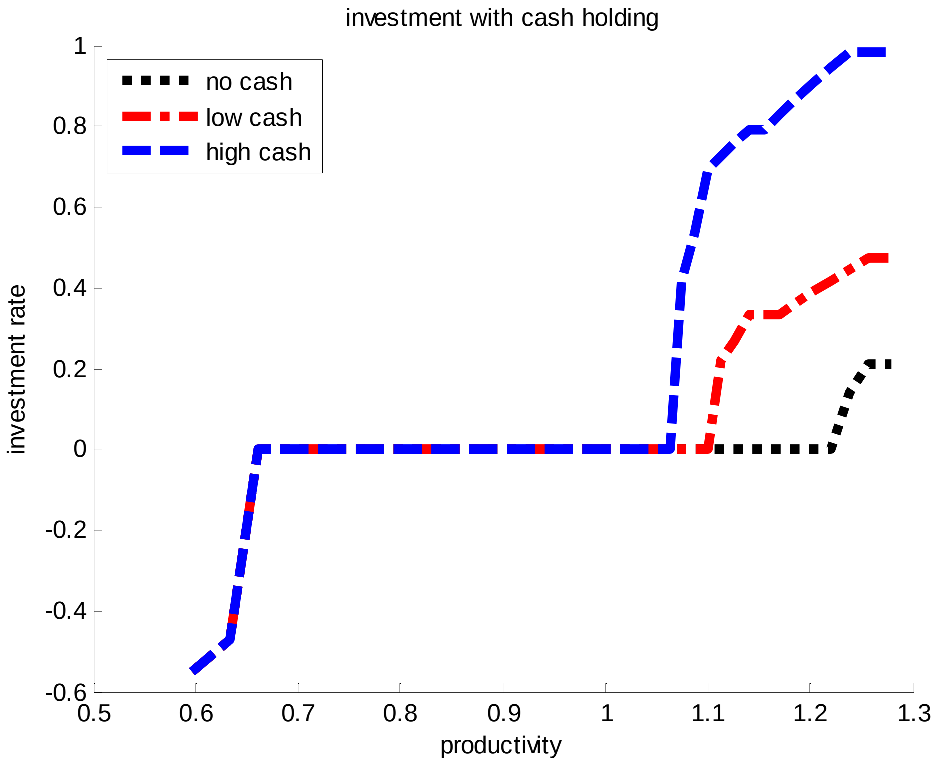
To construct the 95% confidence band, I randomly draw 10,000 times from $(\alpha, \gamma_0, \gamma_1, \gamma_2, \gamma_3)$ from from a multivariate normal distribution with their estimated coefficients and variance-covariance matrix from equation (.29). I also randomly draw 10,000 times from $\phi$ from from a normal distribution with the estimated coefficient and variance-covariance matrix from equation (.30). Then I calculate the $\left(\frac{I}{K}\right)_{it}$, $\left(\frac{I}{K}\right)_{it+1}$, $\left(\frac{I}{K}\right)_{it+2}$, $\left(\frac{I}{K}\right)_{it+3}$ from the above equations (.31), (.32), (.33) and (.34) using the randomly drawn coefficients, sort them. The 95% confidence interval is defined by the bottom 2.5% up to the top 97.5% of the sorted series.

FIGURE .1: POLICY FUNCTION: INVESTMENT UNDER VARIOUS FINANCING COST (NO CASH)



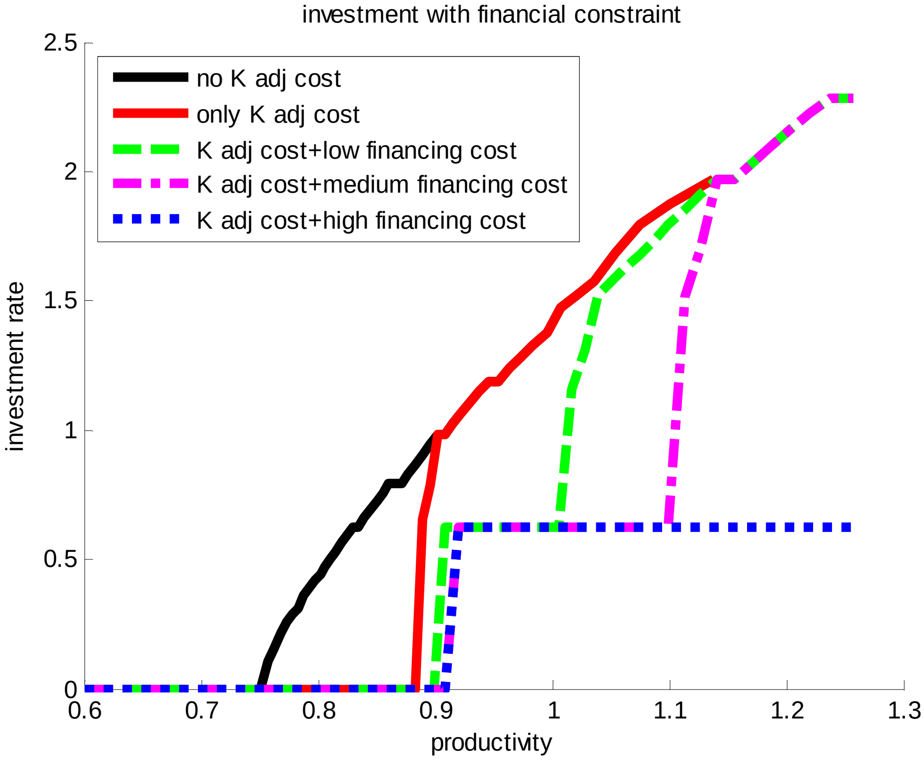

This figure depicts five optimal responses of investment rate (investment-to-capital ratio) in response to the productivity shock, $A$, in the profit function $AK^{\theta}$, conditional on the mean value of capital and zero cash holding. The different curves correspond to firms' response with different adjustment costs. The first (smoothest) curve is the response from firms with no cost of capital adjustment or external financing cost. The curve with the smallest region of zero investment corresponds to the optimal investment from firms with only capital adjustment cost. The curve with the second smallest region of zero investment corresponds to the optimal investment from firms with capital adjustment cost and low financing cost. The curve with the second largest region of zero investment corresponds to the optimal investment from firms with capital adjustment cost and medium financing cost (baseline model). The curve with the the largest region of zero investment corresponds to the optimal investment from firms with capital adjustment cost and high financing cost.

FIGURE .2: POLICY FUNCTION: INVESTMENT UNDER VARIOUS CASH HOLDING



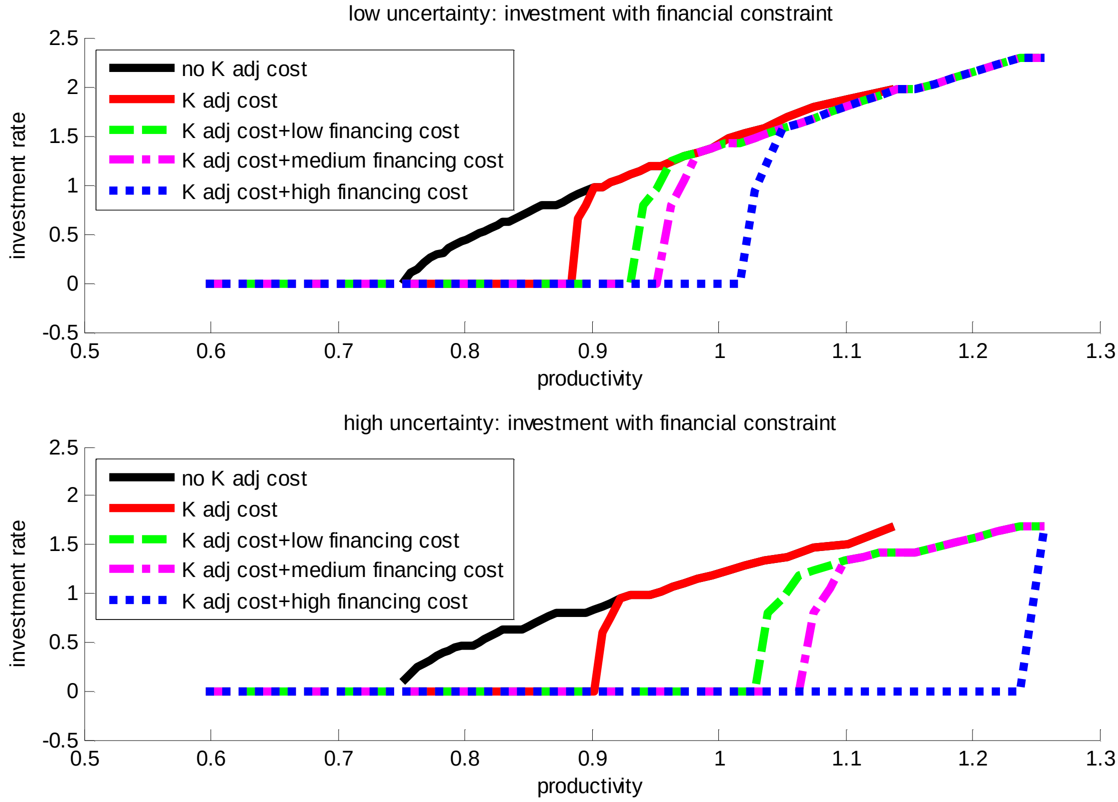

This figure depicts five optimal responses of investment rate (investment-to-capital ratio) in response to the productivity shock, $A$, in the profit function $AK^{\theta}$, conditional on the mean value of capital and the baseline external financing cost. The different curves correspond to firms' response with different cash holdings at beginning of the period. The first curve from the right is the response from firms with no cash holding. The second curve from the right is the response from firms with low cash holding. The third curve from the right is the response from firms with high cash holding.

Figure .3: Policy Function: Investment under Various Financial Constraints (with Cash Holding)



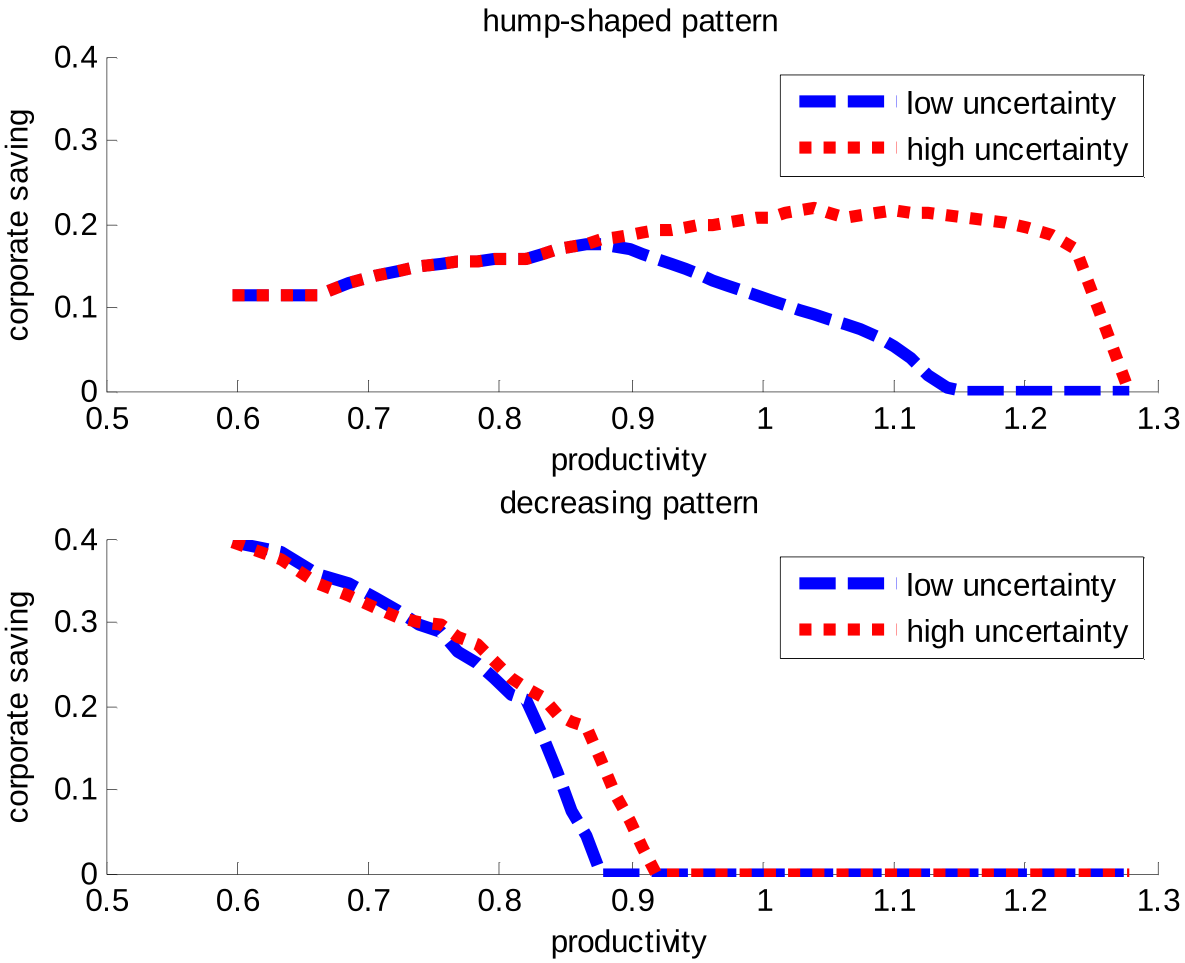

This figure depicts five optimal responses of investment rate (investment-to-capital ratio) in response to the productivity shock, $A$, in the profit function $AK^{\theta}$, conditional on the mean value of capital and mean value of cash holding. The different curves correspond to firms' response with different adjustment costs. The first (smoothest) curve is the response from firms with no cost of capital adjustment or external financing cost. The curve with the smallest region of zero investment corresponds to the optimal investment from firms with only capital adjustment cost. The curve with the second smallest region of zero investment corresponds to the optimal investment from firms with capital adjustment cost and low financing cost. The curve with the second largest region of investment inertia corresponds to the optimal investment from firms with capital adjustment cost and medium financing cost (baseline model). The curve with the the largest region of investment inertia corresponds to the optimal investment from firms with capital adjustment cost and high financing cost.

FIGURE .4: POLICY FUNCTION: INVESTMENT UNDER VARIOUS FINANCIAL CONSTRAINTS (LOW AND HIGH UNCERTAINTY)



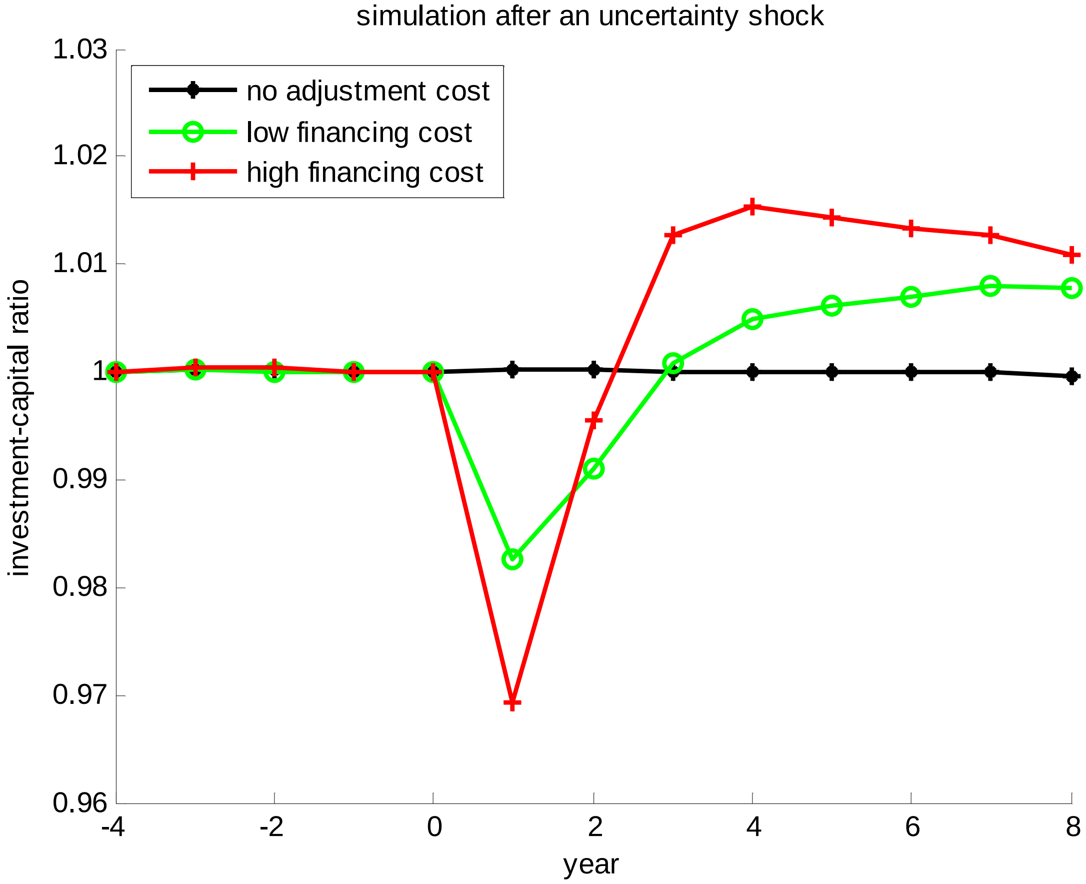

This figure shows investment policy functions under the low-uncertainty regime (top) and the high-uncertainty regime (bottom). Each graph depicts five optimal responses of investment rate (investment-to-capital ratio) in response to the productivity shock, $A$, in the profit function $AK^{\theta}$. The different curves correspond to firms' response with different adjustment costs. The first (smoothest) curves in both graphs are the responses from firms with no cost of capital adjustment or external financing cost. The curves in both graphs with the smallest region of zero investment corresponds to the optimal investment from firms with only capital adjustment cost. The curves in both graphs with the second smallest region of zero investment correspond to the optimal investment from firms with capital adjustment cost and low financing cost. The curves in both graphs with the second largest region of investment inertia correspond to the optimal investment from firms with capital adjustment cost and medium financing cost (baseline model). The curves in both graphs with the the largest region of investment inertia correspond to the optimal investment from firms with capital adjustment cost and high financing cost.

FIGURE .5: POLICY FUNCTION: INVESTMENT UNDER VARIOUS CASH HOLDING



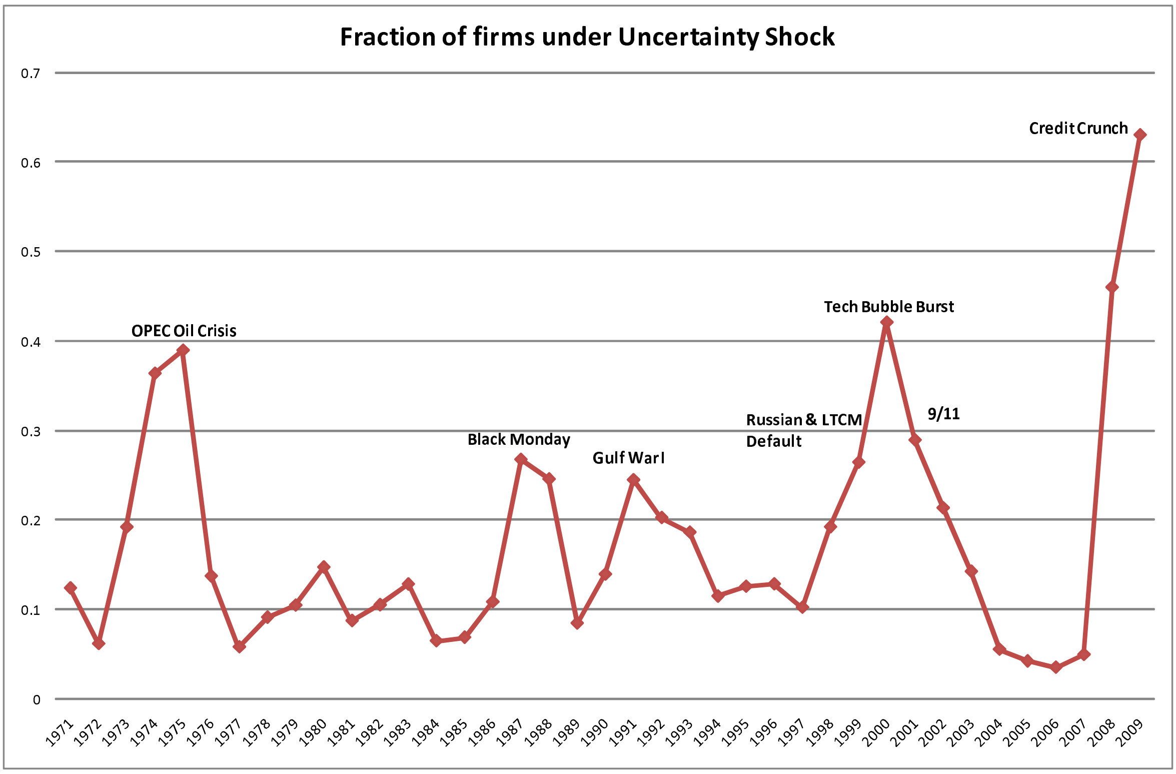

This figure depicts five optimal cash holdings in response to the productivity shock, $A$, in the profit function $AK^{\theta}$, for the hump-shaped cash-holding policy function (top) and the decreasing cash-holding policy function (bottom). In each graph, different curves correspond to firms' response under different uncertainty regimes. The curves on the top of the others show the cash-holding policy functions in the low uncertainty regime, whereas the other curves show the cash-holding policy functions in the high uncertainty regime.

Figure .6: Simulation after An Uncertainty Shock



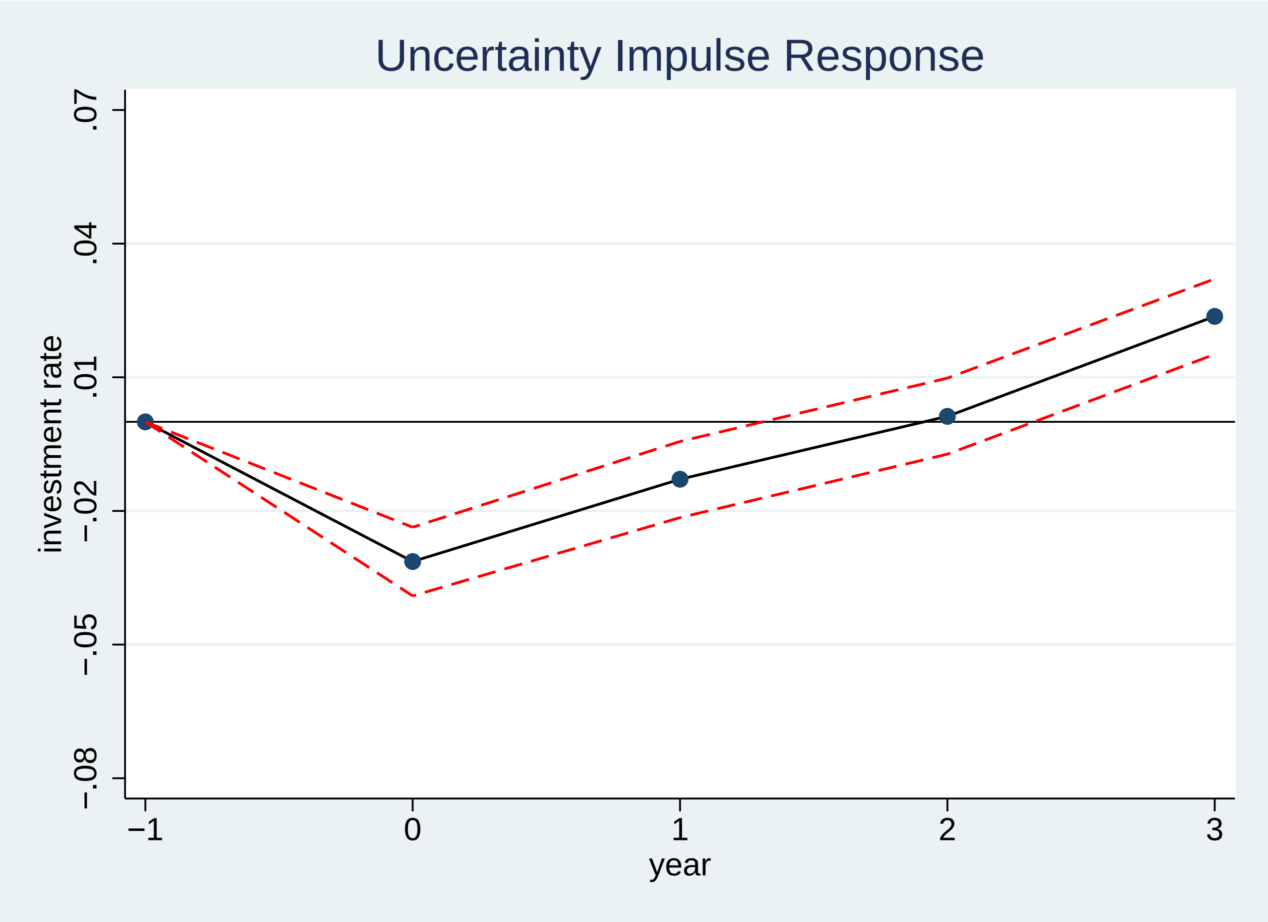

This figure depicts the impulse response of firms' investment rate (investment-to-capital ratios) after a switch from a low uncertainty regime to high uncertainty regime. The three curves correspond to firms with different adjustment costs. The most smooth curve is the investment response from the firm with no adjustment cost. The most variable investment response corresponds to the firm with high financing cost. The third curve is the investment response of a firm with low financing cost. Each firm is assumed to have 300 production units. Year 0 is the year in which uncertainty switch to the high-uncertainty regime. For each category, I run simulations for 300 firms for 20 years at annual frequency with a burn-in period of 180 years to ensure that they are in steady state.

FIGURE .7: FRACTION OF FIRMS UNDER HIGH UNCERTAINTY



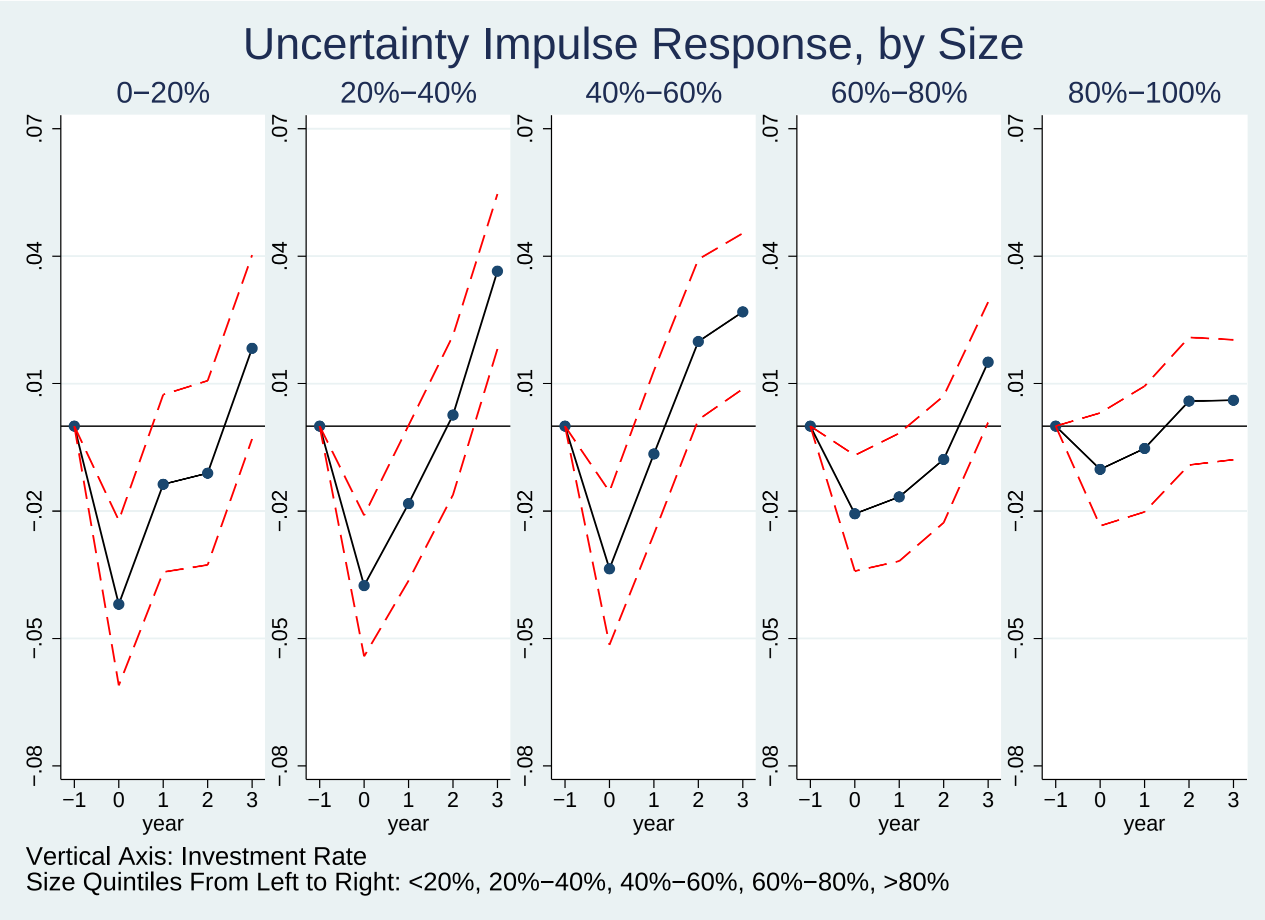

This figure depicts the fraction of firms in the high uncertainty state over the sample periods 1971-2009. Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT . A firm is defined to be in the state of high uncertainty in a given year as a firm with measured uncertainty (standard deviation of daily equity returns) at least one standard deviation higher than its mean uncertainty over all the company's sample years.

Figure .8: Uncertainty Impulse Response for All Firms



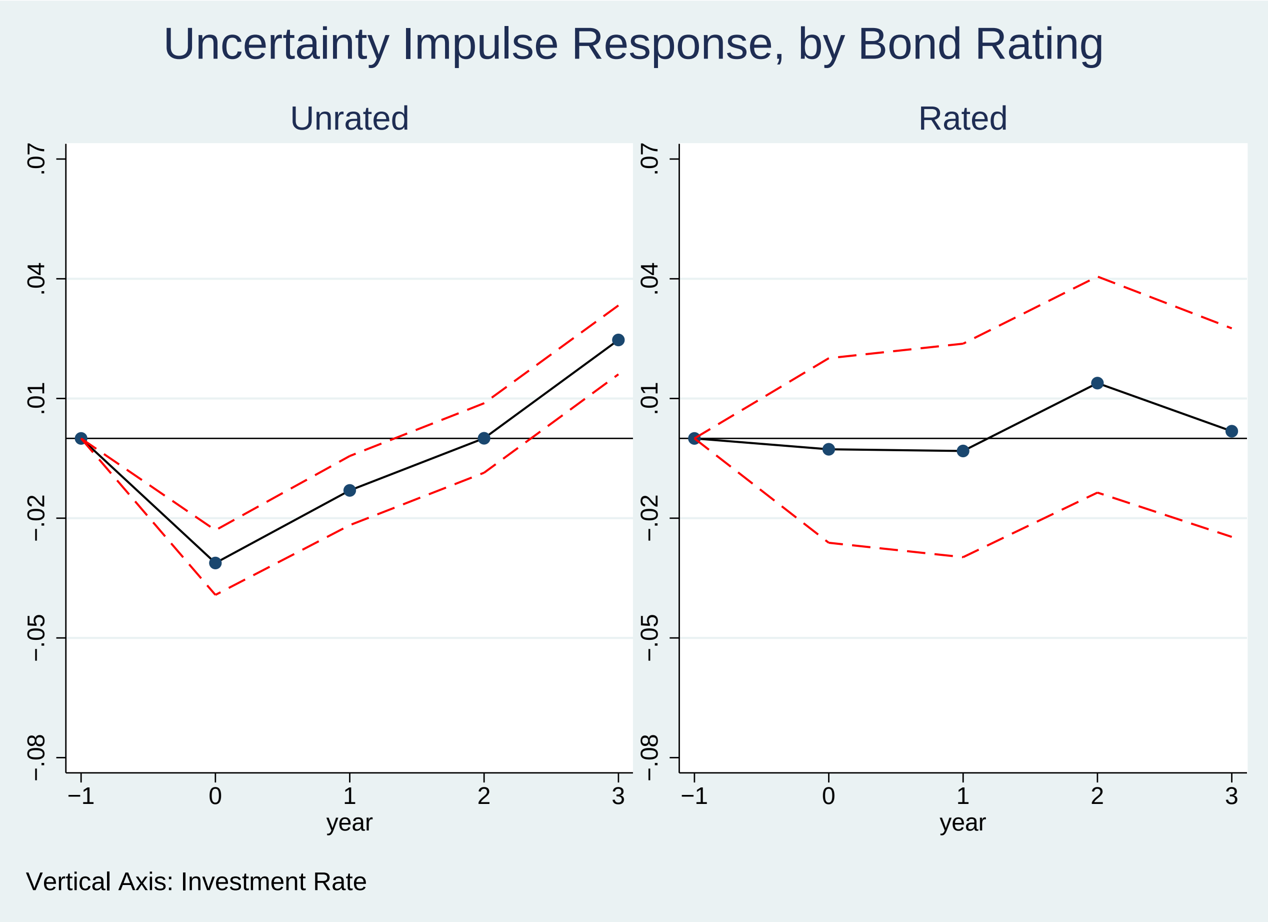

This figure depicts the investment impulse response after a one-standard-deviation increase in uncertainty for all firms in the sample. Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. Year 0 is the year of uncertainty increase. The dotted lines are bootstrapped 95% confidence bands. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$.

FIGURE .9: UNCERTAINTY IMPULSE RESPONSE ACROSS VARIOUS SIZES



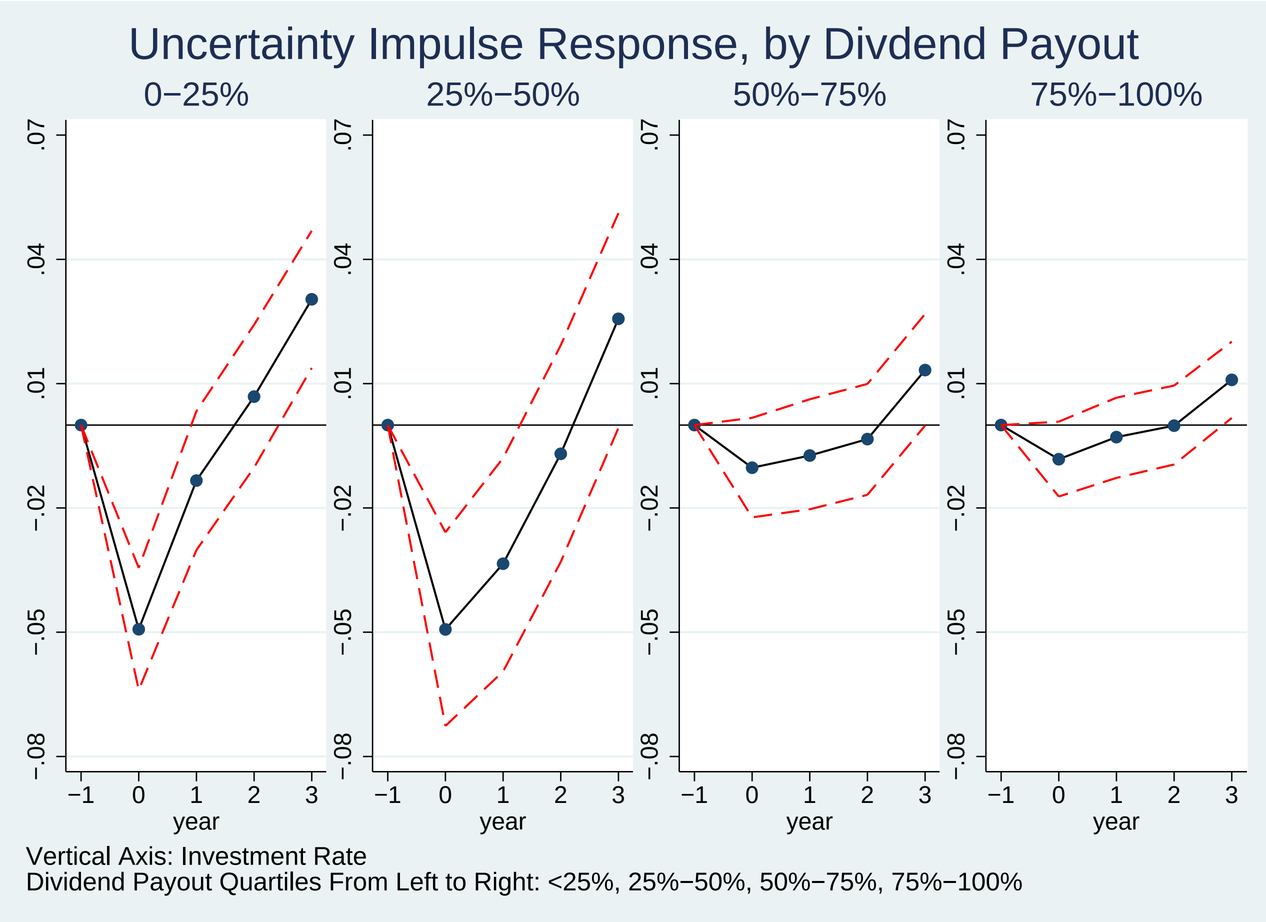

This figure depicts the investment impulse response after a one-standard-deviation increase in uncertainty for five size-subsamples. The sample split is based on size (asset) quintiles. Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. Year 0 is the year of uncertainty increase. The dotted lines are bootstrapped 95% confidence bands. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$.

Figure .10: Uncertainty Impulse Response for Firms with and without Bond Rating




This figure depicts the investment impulse response after a one-standard-deviation increase in uncertainty for two rating-subsamples. The sample split is based on whether a firm is credit rated or not. Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. Year 0 is the year of uncertainty increase. The dotted lines are bootstrapped 95% confidence bands. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$.

FIGURE .11: UNCERTAINTY IMPULSE RESPONSE FOR VARIOUS DIVIDEND PAYOUT




This figure depicts the investment impulse response after a one-standard-deviation increase in uncertainty for four dividend-payout subsamples. The sample split is based on the amount of dividend payout. Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. Year 0 is the year of uncertainty increase. The dotted lines are bootstrapped 95% confidence bands. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$.

Table .1: Model Parameters

| Parameters | Value | Related Literature |
|---|---|---|
| Productivity: | | |
| $\theta$ | 0.75 | Riddick and Whited (2009) |
| $\delta$ | 0.12 | Cooper and Haltiwanger (2006) |
| $\mu$ | 0.02 | Bloom (2009) |
| $\rho$ | 0.885 | Bloom (2009), Cooper and Haltiwanger (2006) |
| Discounting | | |
| $\tau$ | 0.05 | Riddick and Whited (2009) |
| $r$ | 0.04 | Riddick and Whited (2009) |
| Uncertainty: | | |
| $\sigma_L$ | 0.128 | Bloom (2009) |
| $\sigma_H$ | 0.256 | Bloom (2009) |
| $p^{\sigma}_{HH}$ | 0.15 | Bloom (2009) |
| $p^{\sigma}_{LH}$ | 1/3 | Bloom (2009) |
| Capital Adjustment | | |
| $\psi_0$ | 0.039 | Cooper and Haltiwanger (2006), Riddick and Whited (2009) |
| $\psi_1$ | 0.049 | Cooper and Haltiwanger (2006), Riddick and Whited (2009) |
| Financing Cost | | |
| $\lambda_0$ | 0.0389 | Hennessy and Whited (2007), Riddick and Whited (2009) |
| $\lambda_1$ | 0.053 | Hennessy and Whited (2007), Riddick and Whited (2009) |
| $\lambda_2$ | 0.0002 | Hennessy and Whited (2007), Riddick and Whited (2009) |

$\theta$ of the profit function is based on the estimates of labor shares. $\delta$ is the capital depreciation rate. $\mu$and $\rho$ are the drift and persistence of the AR(1) technology process: $\log(A_{t+1}) = \mu + \rho \log(A_t) + v_t$. $\tau$ is the tax penalty of cash holding. $r$ is the discount rate. $\sigma_L$, $\sigma_H$ are the value of low and high uncertainty from the Markov process of uncertainty. $p^{\sigma}_{HH}$ is the transition probability from a high uncertainty regime to a high uncertainty regime. $p^{\sigma}_{LH}$ is the transition probability from a low uncertainty regime to a high uncertainty regime. $\psi_0$ is the value of fixed capital adjustment cost. $\psi_1$ is the coefficient on the quadratic adjustment cost as in $C(I_t, K_t) = \mathbf{1}\{I_t \neq 0\}\psi_0 K_t + \frac{\psi_1}{2}\left(\frac{I_t}{K_t}\right)^2 K_t$. $\lambda_0$ is the fixed external financing cost, $\lambda_1$ is the coefficient on the linear component of the external financing cost and $\lambda_2$ is the quadratic component of the external financing cost: $\Phi(g_t) = \left(\lambda_0 + \lambda_1 g_t + \frac{1}{2}\lambda_2 g_t^2\right)\mathbf{1}\{g_t > 0\}$. All the parameters are calibrated annually. Bloom's (2009) parameters are in monthly frequencies and they are converted to annual frequencies.

Table .2: Summary Statistics for All Firms

| | Investment | Uncertainty | Asset | Capital Stock | Cash Flow | Tobin's Q | Cash |
|---|---|---|---|---|---|---|---|
| Mean | 0.252 | 0.038 | 613 | 684.2 | 0.33 | 2.19 | 1.87 |
| Median | 0.176 | 0.033 | 60 | 50.6 | 0.28 | 1.27 | 0.24 |
| Standard Deviation | 0.236 | 0.022 | 6916 | 1982 | 3.18 | 2.39 | 4.83 |
| # Observations | 37678 | 74439 | 74472 | 46714 | 37618 | 55168 | 37676 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. Firm investment (capital expenditure), cash flow, cash holding are normalized by the replacement value of capital stock at the end of last fiscal year. An average measure of Tobin's Q (Hayashi (1982)) is constructed by dividing the market value by the capital replacement value. Uncertainty is measured by the standard deviation of daily equity returns.

Table .3: Regressions for All Firms

| | Investment-to-Capital Ratio | | | Investment Rate Growth | | |
|---|---|---|---|---|---|---|
| Dependent Variable: | (1) | (2) | (3) | (4) | (5) | (6) |
| I/K | OLS | FE | DPM | OLS | FE | DPM |
| sigma | -1.29*** | -1.67*** | -1.625*** | -3.46*** | -4.34*** | -4.29*** |
| | (0.325) | (0.211) | (0.772) | (0.455) | (0.573) | (2.78) |
| Observations | 30,106 | 30,106 | 23,510 | 30,106 | 30,106 | 18,537 |
| R-squared | 0.104 | 0.064 | | 0.082 | 0.105 | |
| Arellano & Bond Test | | | 0 | | | 0 |
| Hansen Test | | | 0 | | | 0 |
| Number of firms | | 6,578 | 4,968 | | 6,578 | 3,822 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. Robust standard errors are reported in parentheses. *** denotes the case where P-value is less than 0.01; ** is the case where P-value is less than 0.05. * is when P-value is less than 0.1. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$. Investment rate growth is defined as the percentage change in investment rate. All regressions control for lags of investment rate, sigma (uncertainty), cash flow and their interactions with sigma. Fixed effects (FE) models control for the firm fixed-effects. The dynamic panel models (DPM) first differences all the variable for GMM estimations. Instrument validity is tested using the Hansen test of the overidentification restrictions. Serial correlation is tested using a Lagrange multiplier test on the first-difference residuals (Arellano and Bond (1991)). Arellano & Bond Test and Hansen Test report the P-value.

TABLE .4: SUMMARY STATISTICS FOR FIRMS IN EACH SIZE DECILE

| Asset Percentiles: | 0-10% | 10%-20% | 20%-30% | 30%-40% | 40%-50% | 50%-60% | 60%-70% | 70%-80% | 80%-90% | 90%-100% |
|---|---|---|---|---|---|---|---|---|---|---|
| I/K | | | | | | | | | | |
| mean | 0.245 | 0.246 | 0.236 | 0.232 | 0.249 | 0.245 | 0.236 | 0.242 | 0.230 | 0.212 |
| standard deviation | 0.731 | 0.680 | 0.649 | 0.602 | 0.617 | 0.624 | 0.523 | 0.518 | 0.511 | 0.392 |
| sigma | | | | | | | | | | |
| mean | 0.052 | 0.047 | 0.044 | 0.042 | 0.039 | 0.037 | 0.034 | 0.032 | 0.029 | 0.025 |
| standard deviation | 0.027 | 0.026 | 0.024 | 0.022 | 0.020 | 0.020 | 0.018 | 0.016 | 0.016 | 0.012 |
| cf/K | | | | | | | | | | |
| mean | -0.273 | 0.069 | 0.254 | 0.238 | 0.354 | 0.410 | 0.509 | 0.490 | 0.517 | 0.364 |
| standard deviation | 2.318 | 2.015 | 1.625 | 1.829 | 1.686 | 1.612 | 1.419 | 1.242 | 1.244 | 0.818 |
| Asset | | | | | | | | | | |
| mean | 5 | 14 | 26 | 40 | 62 | 103 | 157 | 289 | 645 | 4794 |
| standard deviation | 7 | 23 | 58 | 48 | 76 | 185 | 224 | 332 | 766 | 5432 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. The sample splits to subsamples by ten size (asset) deciles. Firm investment (capital expenditure) and cash flow (cf) are normalized by the replacement value of capital stock (K) at the end of last fiscal year. Uncertainty is measured by the standard deviation of daily equity returns.

TABLE .5: REGRESSIONS FOR FIRMS IN EACH SIZE DECILE

| Dependent Variable: I/K | (1) 0-20% | (2) 20%-40% | (3) 40%-60% | (4) 60%-80% | (5) 80%-100% |
|---|---|---|---|---|---|
| | | **OLS:** | | | |
| σ | -1.55*** | -1.37*** | -1.24*** | -1.21*** | -0.57 |
| | (0.49) | (0.75) | (0.65) | (0.83) | -0.72 |
| | | **Fixed Effect:** | | | |
| σ | -1.85*** | -1.75*** | -1.73*** | -1.37* | -0.94 |
| | (0.56) | (0.68) | (0.77) | (0.75) | -0.95 |
| | | **Dynamic Panel:** | | | |
| σ | -2.01** | -2.45*** | -2.43*** | -2.37* | -0.74 |
| | (1.51) | (1.33) | (1.37) | (1.75) | -0.98 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. The sample splits to subsamples by ten size (asset) deciles. Robust standard errors are reported in parentheses. *** denotes the case where P-value is less than 0.01; ** is the case where P-value is less than 0.05. * is when P-value is less than 0.1. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$. Investment rate growth is defined as the percentage change in investment rate. All regressions control for lags of investment rate, sigma (uncertainty), cash flow and their interactions with sigma. Fixed effects models control for the firm fixed-effects. The dynamic panel models (DPM) first differences all the variable for GMM estimations.

Table .6: Summary Statistics for Firms with and without Bond Ratings

| | No Bond Rating | Bond Rating |
|---|---|---|
| I/K | | |
| mean | 0.24 | 0.20 |
| standard deviation | 0.61 | 0.36 |
| # obs | 35870 | 1808 |
| sigma | | |
| mean | 0.04 | 0.02 |
| standard deviation | 0.02 | 0.01 |
| # obs | 69032 | 5407 |
| cf/K | | |
| mean | 0.29 | 0.43 |
| standard deviation | 1.70 | 0.86 |
| # obs | 35822 | 1796 |
| Asset | | |
| mean | 349 | 3983 |
| standard deviation | 1502 | 5277 |
| # obs | 69062 | 5410 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2006. The sample splits to subsamples by whether firms have a credit rating over their sample periods. Firm investment (capital expenditure) and cash flow (cf) are normalized by the replacement value of capital stock (K) at the end of last fiscal year. Uncertainty is measured by the standard deviation of daily equity returns.

Table .7: Regressions for Firms with and without Bond Ratings

| | OLS | | Fixed Effect | | Dynamic Panel | |
|---|---|---|---|---|---|---|
| Dependent Variable: | (1) | (2) | (3) | (4) | (5) | (6) |
| I/K | Unrated | Rated | Unrated | Rated | Unrated | Rated |
| sigma | -1.45*** | 0.227 | -1.615*** | -0.254 | -2.12*** | -2.146 |
| | (0.338) | (3.257) | (0.349) | (2.089) | (1.420) | (5.107) |
| Observations | 28,636 | 1,470 | 28,636 | 1,470 | 20,911 | 1,118 |
| R-squared | 0.103 | 0.382 | 0.064 | 0.314 | | |
| Arellano & Bond Test | | | | | 0 | 0.02 |
| Hansen Test | | | | | 0 | 1 |
| Number of firms | | | 6,345 | 348 | 4,530 | 252 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2006. The sample splits to subsamples by whether firms have a credit rating (Rated) over their sample periods. Robust standard errors are reported in parentheses. *** denotes the case where P-value is less than 0.01; ** is the case where P-value is less than 0.05. * is when P-value is less than 0.1. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$. Investment rate growth is defined as the percentage change in investment rate. All regressions control for lags of investment rate, sigma (uncertainty), cash flow and their interactions with sigma. Fixed effects models control for the firm fixed-effects. The dynamic panel models (DPM) first differences all the variable for GMM estimations. Instrument validity is tested using the Hansen test of the overidentification restrictions. Serial correlation is tested using a Lagrange multiplier test on the first-difference residuals (Arellano and Bond (1991)). Arellano & Bond Test and Hansen Test report the P-value.

Table .8: Summary Statistics for Firms in Each Dividend Quartile

| | 0-25% | 25%-50% | 50%-75% | 75%-100% |
|---|---|---|---|---|
| I/K | | | | |
| mean | 0.28 | 0.24 | 0.21 | 0.20 |
| standard deviation | 0.70 | 0.64 | 0.52 | 0.40 |
| # obs | 16394 | 4288 | 9584 | 7372 |
| sigma | | | | |
| mean | 0.05 | 0.04 | 0.03 | 0.02 |
| standard deviation | 0.02 | 0.02 | 0.02 | 0.01 |
| # obs | 29160 | 8031 | 18599 | 18595 |
| cf/K | | | | |
| mean | 1.51 | 2.65 | 0.48 | 4.76 |
| standard deviation | 2.75 | 1.85 | 1.32 | 0.80 |
| # obs | 16367 | 4288 | 9582 | 7341 |
| Asset | | | | |
| mean | 170 | 68 | 117 | 2034 |
| standard deviation | 673 | 266 | 265 | 4051 |
| # obs | 29179 | 8034 | 18603 | 18602 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. The sample splits to four subsamples by the amount of dividend payout. Firm investment (capital expenditure) and cash flow (cf) are normalized by the replacement value of capital stock (K) at the end of last fiscal year. Uncertainty is measured by the standard deviation of daily equity returns.

Table .9: Regressions for Firms in Each Dividend Quartile

| Dependent Variable: I/K | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | 0-25% | 25%-50% | 50%-75% | 75%-100% |
| | **OLS** | | | |
| sigma | -1.981*** | -1.692*** | -0.448* | -0.265 |
| | (0.248) | (0.498) | (0.471) | (0.501) |
| Observations | 12,476 | 3,560 | 8,033 | 6,010 |
| R-squared | 0.097 | 0.132 | 0.148 | 0.282 |
| | **Fixed Effect** | | | |
| sigma | -1.705*** | -1.703*** | -0.929*** | -0.181 |
| | (0.272) | (0.381) | (0.254) | (0.353) |
| Observations | 12,476 | 3,560 | 8,033 | 6,010 |
| R-squared | 0.074 | 0.091 | 0.094 | 0.210 |
| Number of firms | 3,415 | 647 | 1,373 | 1,131 |
| | **Dynamic Panel** | | | |
| sigma | -0.205 | -2.99*** | -2.083*** | 0.351 |
| | (1.001) | (1.602) | (1.092) | (1.462) |
| Observations | 9,049 | 2,913 | 6,657 | 4,876 |
| Arellano & Bond Test | 0 | 0 | 0 | 0 |
| Hansen Test | 0 | 0 | 0 | 0 |
| Number of firms | 2,388 | 546 | 1,145 | 882 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. The sample splits to four subsamples by the amount of dividend payout. Robust standard errors are reported in parentheses. *** denotes the case where P-value is less than 0.01; ** is the case where P-value is less than 0.05. * is when P-value is less than 0.1. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$. Investment rate growth is defined as the percentage change in investment rate. All regressions control for lags of investment rate, sigma (uncertainty), cash flow and their interactions with sigma. Fixed effects models control for the firm fixed-effects. The dynamic panel models (DPM) first differences all the variable for GMM estimations. Instrument validity is tested using the Hansen test of the overidentification restrictions. Serial correlation is tested using a Lagrange multiplier test on the first-difference residuals (Arellano and Bond (1991)). Arellano & Bond Test and Hansen Test report the P-value.

Table .10: Summary Statistics for Firms in Each KZ Decile

| Asset Percentiles: | 0-10% | 10%-20% | 20%-30% | 30%-40% | 40%-50% | 50%-60% | 60%-70% | 70%-80% | 80%-90% | 90%-100% |
|---|---|---|---|---|---|---|---|---|---|---|
| I/K | | | | | | | | | | |
| mean | 0.19 | 0.22 | 0.24 | 0.25 | 0.24 | 0.25 | 0.25 | 0.25 | 0.25 | 0.26 |
| standard deviation | 0.48 | 0.50 | 0.56 | 0.56 | 0.58 | 0.62 | 0.64 | 0.62 | 0.65 | 0.72 |
| sigma | | | | | | | | | | |
| mean | 0.03 | 0.03 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 | 0.05 |
| standard deviation | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.03 |
| cf/K | | | | | | | | | | |
| mean | 0.72 | 0.63 | 0.57 | 0.51 | 0.46 | 0.33 | -0.90 | 0.28 | 0.31 | -0.19 |
| standard deviation | 1.15 | 1.43 | 1.73 | 1.81 | 1.62 | 1.48 | 1.79 | 1.83 | 2.31 | 2.29 |
| Asset | | | | | | | | | | |
| mean | 1086 | 634 | 517 | 634 | 785 | 471 | 574 | 467 | 461 | 446 |
| standard deviation | 3520 | 2302 | 1869 | 2156 | 2567 | 1745 | 2044 | 1648 | 1653 | 1959 |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. The sample splits to ten subsamples by the Kaplan-Zingales index. The Kaplan-Zingales index provides a score of financial constraint based upon various variables: $-1.001909\frac{CF_{it}}{A_{it-1}} + 3.139193LEV_{it} - 39.3678\frac{DIV_{it}}{A_{it-1}} - 1.314759\frac{C_{it}}{A_{ti-1}} + 0.2826389Q_{it}$. Firm investment (capital expenditure) and cash flow (cf) are normalized by the replacement value of capital stock (K) at the end of last fiscal year. Uncertainty is measured by the standard deviation of daily equity returns.

Table .11: Regressions for Firms in Each KZ Decile

| (1) 0-10% | (2) 10%-20% | (3) 20%-30% | (4) 30%-40% | (5) 40%-50% | (6) 50%-60% | (7) 60%-70% | (8) 70%-80% | (9) 80%-90% | (10) 90%-100% |
|---|---|---|---|---|---|---|---|---|---|
| | | | | OLS | | | | | |
| 0.62 | -0.98*** | -0.765*** | -1.022*** | -1.591*** | -1.073*** | -1.769*** | -1.709*** | -1.668*** | -1.469*** |
| (0.793) | (0.825) | (0.597) | (0.542) | (0.718) | (0.718) | (0.664) | (0.596) | (0.458) | (0.403) |
| | | | | Fixed Effect | | | | | |
| 0.71 | -1.32*** | -0.553*** | -0.838*** | -1.404*** | -0.775*** | -2.447*** | -2.129*** | -1.819*** | -1.733*** |
| (0.852) | (0.899) | (0.507) | (0.556) | (0.641) | (0.774) | (0.810) | (0.669) | (0.624) | (0.502) |
| | | | | Dynamic Panel | | | | | |
| -0.25 | -1.467* | -0.57 | -0.96 | -2.304** | -0.71 | -3.257*** | -2.688*** | -2.320*** | -2.617*** |
| (1.461) | (1.335) | (1.400) | (1.212) | (1.901) | (2.083) | (1.791) | (1.642) | (2.040) | (1.568) |

Calculations are based on a sample of publicly-traded nonfinancial firms from COMPUSTAT from 1971 to 2009. The sample splits to ten subsamples by the Kaplan-Zingales index. The Kaplan-Zingales index provides a score of financial constraint based upon various variables: $-1.001909\frac{CF_{it}}{A_{it-1}} + 3.139193LEV_{it} - 39.3678\frac{DIV_{it}}{A_{it-1}} - 1.314759\frac{C_{it}}{A_{ti-1}} + 0.2826389Q_{it}$. Robust standard errors are reported in parentheses. *** denotes the case where P-value is less than 0.01; ** is the case where P-value is less than 0.05. * is when P-value is less than 0.1. Investment rate is the investment-to-capital ratio $\frac{I_t}{K_{t-1}}$. Investment rate growth is defined as the percentage change in investment rate. All regressions control for lags of investment rate, sigma (uncertainty), cash flow and their interactions with sigma. Fixed effects models control for the firm fixed-effects. The dynamic panel models (DPM) first differences all the variable for GMM estimations. Instrument validity is tested using the Hansen test of the overidentification restrictions. Serial correlation is tested using a Lagrange multiplier test on the first-difference residuals (Arellano and Bond (1991)). Arellano & Bond Test and Hansen Test report the P-value.

# Chapter 2

# Taxation and Income Shifting: Empirical Evidence from a Natural Experiment from China Co-authored with Zhiyong An

## 2.1 Introduction

Cross-border investment by multinational corporations (MNCs) is one of the most salient features of today's global economy. Countries around the world have made numerous tax concessions to attract MNCs' investments. Such cross-country differences in corporate tax rates are an enduring feature of the global fiscal environment. Only multinational corporations are able to benefit from the cross-country differences in corporate tax rates to reduce their overall tax burden by shifting income from high-tax countries to low-tax countries. Multinational corporations (MNCs) are taking advantage of the cross-country differences in corporate tax rates to reduce their overall tax burden by shifting income from high-tax countries to low-tax countries. However, whether or to what extent they engage in this behavior has long been the subject of much debate.

By their very nature, MNCs trade goods, services, and intangible assets across national borders within their enterprises. MNCs typically can reduce their overall tax burden by artificially reducing transfer prices charged by affiliates in high-tax countries for goods, services, and intangible assets provided to affiliates in low-tax countries. In order to stem the flow of taxation revenues overseas and to ensure that they get to tax their fair share, most countries enforce tax laws based on the *arm's length principle*, which requires transfer prices for transactions between different parts of the same MNC to be set at the same level as prices for similar transactions between unrelated parties. However, strict application of the arm's length principle is often problematic in practice. For example, for many intra-corporation transactions there exists no comparable market outside the corporation. This is in particular the case for intellectual property or knowledge-intensive intermediate goods that are developed or produced by one part of a MNC and used by other parts of the same MNC in other countries.

MNCs' income shifting behavior has long been documented and studied. Wheeler (1988) presents U.S. tax court cases where income was shifted for tax reasons. In one case, in 1975 G. D. Searle & Company had an average return on employed assets of -42.3% in the U.S. and 119% in Puerto Rico whose effective tax rate is zero. Theoretically, Horst (1971) builds a simple model that shows how MNCs choose transfer prices in order to maximize their after-tax earnings. Horst's model analyzes the choices of a monopolistic corporation that sells in two countries simultaneously. The corporation's earnings are equal to the sum of its after-tax profits in the two countries and a term that shows the impact of intra-corporation trade. The optimal transfer price chosen by the corporation to maximize its after-tax earnings is either the lowest transfer price or the highest transfer price, depending on a comparison of the relative differential in tax rates between the importing and exporting countries with the tariff rate.

In a series of efforts over the past two decades, there has been systematic empirical evidence uncovered for income shifting. Almost all of the earlier empirical studies on income shifting concern the U.S. and, more specifically, income shifting from the U.S. to low-tax countries (e.g., Grubert and Mutti (1991); Grubert et al. (1993); Klassen et al.(1993); Hines and Rice(1994); Collins et al. (1998); Grubert and Slemrod (1994); Swenson (2001); Clausing (2003))[1]. In the past decade, empirical studies on income shifting have been done for other OECD countries (e.g., Bartelsman and Beetsma (2003); Mintz and Smart (2004); Buettner et al. (2009); Huizinga and Laeven (2008); Weichenrieder (2009)). These studies provide some indirect empirical evidence for tax-induced income shifting. However, to the best of our knowledge, no empirical study on income shifting using data from developing countries and, in particular for China, exists.

China's new *Corporate Income Tax Law* was passed in March 2007 and took effect on January 1st 2008. It terminates the dual corporate income tax regime by removing the tax preferences offered to foreign investment enterprises (FIEs) by the Chinese government and unifies the corporate income tax regime for FIEs and Chinese domestic enterprises (DEs). In this paper we use a difference-in-differences approach to determine whether FIEs are responding to the law by shifting income out of China. We employ the Chinese Industrial Enterprises Database from 2002 to 2008 to implement the analysis. Our treatment group is made up of FIEs affected by the law, while our control group is made up of DEs unaffected by the law. We first show that the trends of the pre-tax profit of the treatment and control groups before the passage of the law are parallel to each other, which implies that the identifying assumption of our identification strategy is satisfied and thus our difference-in-differences analysis has solid foundation. Then we conduct the difference-in-differences

[1]See Hines (1996; 1999) for a review of the literature on income shifting.

regressions. The estimates suggest three conclusions. First, we find that FIEs seem to have responded to the law by shifting income out of China. Second, the magnitude of the response is larger for larger-size enterprises, which might be due to their greater capability of shifting income across countries. Finally, the magnitude of response is larger for Hong Kong-Macau-Taiwan (HMT) investment enterprises than that for other FIEs. Because both Hong Kong and Macau are tax havens (Dharmapala and Hines Jr. (2009)), the pre-tax profit of HMT investment enterprises should be more elastic than that of other FIEs. All the three findings are consistent with tax-induced income shifting.

Our work makes at least three contributions. First, ours is the first paper to focus on income-shifting activities of Chinese enterprises using data from China. Second, our work provides helpful information for Chinese policymakers. Since China opened its door in 1978 and especially since its accession to the World Trade Organization (WTO) in 2001, International transactions have played an important role in the Chinese economy. At the same time, the possible loss in tax revenues due to income shifting by FIEs has increasingly come under the spotlight of China's tax authorities. Over the past few years, the *State Administration of Taxation* (SAT) of China has blamed FIEs for substantial losses in taxation revenues. To the best of our knowledge, no rigorous empirical study has been done to explore the extent to which FIEs shift income out of China. Our work attempts to fill in this gap. Finally, this is the first rigorous study of China's new *Corporate Income Tax Law*, the most profound tax reform of the decade in China.

The remainder of the paper is organized as follows. Section 2 describes the changes in the effective corporate income tax rate brought about by China's new Corporate Income Tax Law. Section 3 presents our identification strategy. Section 4 presents the regression framework and the specification of our econometric models. Section 5 describes the data in detail, and Section 6 reports the results of our data analysis. Finally, Section 7 concludes the chapter.

## 2.2 China's New *Corporate Income Tax Law*

Since the early 1990s, China has maintained a dual corporate income tax regime: one regime for Chinese DEs and the other one for FIEs. Under the dual corporate income tax regime, DEs and FIEs are subject to different effective corporate income tax rates. The effective corporate income tax rate was about 25% for DEs, while it was about 15% for FIEs. The lower effective corporate income tax rate for FIEs was made possible by certain preferential tax treatments offered by the Chinese government for FIEs. The purpose of the dual corporate income tax regime is to entice foreign investment into China.

In order to create a level playing field and a fair fiscal environment that promotes competition and transparency for all enterprises in China and in order to increase the sophistication of China's tax regime in general, the National People's Congress of China drafted and passed the new Corporate Income Tax Law in March 2007. The law came into effect on January

1st 2008. The law is the most profound tax reform of the decade in China. It terminates the dual corporate income tax regime and unifies the corporate income tax rate to 25% for both FIEs and DEs. In other words, it increases the corporate income tax rate for FIEs from about 15% to 25%, while keeps that unchanged at 25% for DEs. Thus, the law has huge impact on FIEs, but basically no impact on DEs.

## 2.3 Identification Strategy

As described in the previous section, China's new *Corporate Income Tax Law* has huge impact on foreign investment enterprises, but basically no impact on domestic enterprises. Therefore, the law presents a great opportunity for us to construct a natural experiment and use a difference-in-differences approach to determine whether foreign investment enterprises are responding to the law by reducing their investment in China. Our treatment group is made up of FIEs affected by the law, while our control group is made up of DEs unaffected by the law.

In order to identify FIEs' investment response to China's new Corporate Income Tax Law, a naïve identification strategy is to compare the assets of FIEs before and after January 1 2008 on which the law came into effect. However, since there may be underlying trends in the assets of FIEs, we use the control group to isolate FIEs' response to the law. In other words, our identification strategy is to compare the change in the assets of the treatment group and that of the control group before and after the law came into effect as a means of deducing FIEs' investment response to the law. This is essentially the difference-in-differences methodology.[2] It controls for the underlying trends in the assets of the treatment group through that of the control group over the period. It is clear to see that the identifying assumption that we make is that there is little difference between the underlying trends in the assets of the treatment and control groups. In other words, we assume that in the absence of China's new Corporate Income Tax Law, the difference between the change in the assets of the treatment group and that of the control group over the period would be equal to zero. We will show that the identifying assumption that we make is satisfied and thus our difference-in-differences analysis has solid foundation.

The change in the pre-tax profit of the treatment group before and after the law came into effect is given by $(Profit_{ta} - Profit_{tb})$, where $t$ means the treatment group, $a$ means "after the law came into effect", and $b$ means "before the law came into effect". Part of this change is due to FIEs' investment response to the law, and part is due to the underlying trends in the pre-tax profit of the treatment group (i.e., FIEs). The identifying assumption that we make is that the underlying trends in the pre-tax profit of the treatment group will be reflected in the change in the pre-tax profit of the control group, given by $(Profit_{ca} - Profit_{cb})$,

[2]See Angrist and Krueger (1999) for an excellent reference for the difference-in-differences methodology associated with the natural experiment approach, and see Card and Krueger (1994) for a nice application of the methodology.

where $c$ means the control group, $a$ means "after the law came into effect", and $b$ means "before the law came into effect". The test that FIEs are responding to the law by reducing their investment in China is a test that shows $(Assets_{ta} - Assets_{tb}) - (Assets_{ca} - Assets_{cb})$ is negative. The identifying assumption that we make essentially says that $(Profit_{ta} - Profit_{tb}) - (Profit_{ca} - Profit_{cb})$ would be equal to zero in the absence of the law. We will show that the identifying assumptions of our identification strategy are satisfied shortly after.

## 2.4 Econometric Models

To examine whether FIEs are responding to China's new *Corporate Income Tax Law* by shifting their income out of China, one could estimate the following difference-in-differences model by employing OLS regression:

$$\begin{aligned} log(Profit) = {} & \alpha + \beta AssetReturn + \lambda EnterpriseScale + \eta DebtRatio \\ & + \delta Z + \gamma_0 treatment + \gamma_1 postlegislation \\ & + \gamma_2 treatment \times postlegislation + \varepsilon \end{aligned} \tag{2.1}$$

where $\varepsilon$ is an error term; $Profit$ is the pre-tax profit. We use $log(Profit)$ as the dependent variable to address the potential nonlinearity problem.

The variable *treatment* is a dummy variable indicating whether an enterprise is included in the treatment group or in the control group, and is equal to one if it is included in the treatment group and is equal to zero if it is included in the control group. The type of registration (denoted as *RegistrationType*) of each enterprise tells us the type of each enterprise. Enterprises in China can be classified into three categories: (1) domestic enterprises; (2) HMT investment enterprises; (3) other FIEs. .1 shows a table of classifications by types of registration. The variable is a dummy variable indicating whether an observation is made after the law came into effect, and is equal to one if it is made after the law came into effect and is equal to zero otherwise. The law was passed in March 2007 and came into effect on January 1 2008. Data for year 2008 makes up our post-legislation observations and data for year 2006 constitutes our pre-legislation observation. We use the data for years from 2002 to 2006 to check whether the identifying assumption of our identification strategy is satisfied.

In order to reduce the residual variance of the regression and produce more efficient estimates, we include a set of control variables. First, because an enterprise's profit might depend on its profitability, we include the return on assets (denoted as *AssetReturn*) as a control variable. We expect the coefficient of *AssetReturn*, namely $\beta$, to be positive and statistically significant.

Second, because an enterprise's profit might also depend on its scale of operations, we include the scale of an enterprise (denoted as *EnterpriseScale*) as a control variable in our econometric model. The categorical variable *EnterpriseScale* has three categories which correspond to large-size enterprises, medium-size enterprises, and small-size enterprises respectively[3]. Because an enterprise's scale of operation should have a positive impact on its profit, we expect to see that the estimated coefficient will increase with the size of the enterprise.

Third, because the post-legislation observation is made in year 2008 in which a global financial crisis occurred, we include the debt ratio of an enterprise (denoted as *DebtRatio*) as one control variable in our econometric model. The higher the debt ratio of an enterprise is, the larger the impact of the 2008 global financial crisis on the enterprise would be. Therefore, we expect the coefficient of *DebtRatio*, namely $\eta$, to be negative and statistically significant.

Finally, $Z$ is a vector of control variables which include: (1) a categorical variable that indicates the area (the counterpart in the U.S. is state) where an enterprise is registered and is denoted as *Location*; and (2) a categorical variable that indicates the two-digit industry category that an enterprise belongs to and is denoted as $Industry$. These two categorical control variables are included to control for industry characteristics and location characteristics of enterprises that may affect the level of pre-tax profit.

The coefficient of the dummy variable , $\gamma_0$, is the treatment group specific effect that accounts for the average permanent differences between the treatment and control groups. The coefficient of the dummy variable *postlegislation*, $\gamma_1$, captures the time trend common to the treatment and control groups. The coefficient of the interaction term $treatment \times postlegislation$, $\gamma_1$, gives us the difference-in-differences estimate of the treatment effect, namely, the difference between the change in $log(Profit)$ of the treatment group and that of the control group before and after the law came into effect. We expect $\gamma_2$ to be negative and statistically significant. In other words, we expect to find that FIEs responded to the law by shifting their income out of China.

Because larger-size enterprises might have more capability to shift income across countries, we expect to see that the magnitude of the response is larger for larger-size enterprises. In order to test this idea, we estimate the following difference-in-differences model:

$$\begin{aligned} log(Profit) = {} & \alpha + \beta AssetReturn + \lambda EnterpriseScale + \eta DebtRatio \\ & + \delta Z + \gamma_0 treatment + \gamma_1 postlegislation \\ & + \gamma_2 treatment \times postlegislation \\ & + \gamma_3 treatment \times postlegislation \times dummyLargeSize \\ & + \gamma_4 treatment \times postlegislation \times dummyMediumSize \\ & + \varepsilon \end{aligned} \tag{2.2}$$

where *Large* is a dummy variable that is equal to one if the enterprise is a large-size

[3]In order to help understand the concept of *EnterpriseScale*, .5 gives the summary statistics of total employees and total assets by *EnterpriseScale* in 2003. By .5, a larger-size enterprise has on average more total employees and more total assets.

enterprise and is equal to zero if otherwise, and $Medium$ is also a dummy variable that is equal to one if the enterprise is a medium-size enterprise and is equal to zero if otherwise.

Note that $\gamma_2$ gives us the treatment effect for small-size enterprises; $\gamma_3$ gives us the difference between the treatment effect for large-size enterprises and that for small-size enterprises; and $\gamma_4$ gives us the difference between the treatment effect for medium-size enterprises and that for small-size enterprises. We expect to find the estimated coefficients $\gamma_2$, $\gamma_3$ and $\gamma_4$ are all negative and statistically significant; and further that $\gamma_3 < \gamma_4$. In other words, we expect to see that FIEs of all sizes are responding to the law by shifting their income out of China; and that the magnitude of the response is larger for larger-size enterprises.

Hong Kong and Macau are on the list of tax havens compiled by Dharmapala and Hines Jr. (2009). We expect that the pre-tax profit of HMT investment enterprises should be more elastic than that of other FIEs. Therefore, we expect to see that the magnitude of the response is larger for HMT investment enterprises than that for other FIEs. In order to test this idea, we estimate the following difference-in-differences model instead of Equation 2.1:

$$\begin{aligned} log(Profit) = {} & \alpha + \beta AssetReturn + \lambda EnterpriseScale + \eta DebtRatio \\ & + \delta Z + \gamma_0 treatment + \gamma_1 postlegislation \\ & + \gamma_2 treatment \times postlegislation \\ & + \gamma_3 treatment \times postlegislation \times DummyHMT + \varepsilon \end{aligned} \tag{2.3}$$

where HMT is a dummy variable that is equal to one if the enterprise is an HMT investment enterprise .1 shows how we impute the value of HMT for our data. Note that gives us the treatment effect for other FIEs that are not HMT investment enterprises. We expect to find that both HMT investment enterprises and other FIEs responded to the law by shifting their income out of China; and the magnitude of the response is larger for HMT investment enterprises than that for other FIEs.

## 2.5 Data Description

We employ the *Chinese Industrial Enterprises Database (2002-2008)* to implement the analysis. The database embodies information of enterprises whose annual sales revenue is above 5 million RMB. The coverage of the database is identical with that of the industrial sector of the *China Statistical Yearbook* and with that of the *China Industry Economy Statistical Yearbook*. The difference is that the Chinese Industrial Enterprises Database is firm-level data, while both the industrial sector of the *China Statistical Yearbook* and the *China Industry Economy Statistical Yearbook* are aggregated data along different dimensions.

By 2008, the database has included more than 410,000 industrial enterprises, which accounts for about 95% of the total industrial output value of China. The database contains about 40 general industry categories at the two-digit industry code level, and covers all the 31 areas in the mainland of China, namely, 22 provinces, 5 autonomous regions (namely, Guangxi, Neimeng, Ningxia, Xinjiang, and Tibet), and 4 cities (namely, Beijing, Tianjin, Shanghai, and Chongqing) that report directly to the central government. The database is the most complete and most authoritative firm-level database in China.

Each enterprise in the database is identified by a unique enterprise ID. The sample of the enterprises in the database changes year by year, with some enterprises entering the database and some others exiting the database. However, most of the enterprises are continuously kept in the database. In other words, the database is roughly a nice panel dataset.

The database provides two types of information for each enterprise. The first type of information is basically qualitative, including the ID of each enterprise, the location where each enterprise is registered, the type of registration of each enterprise, the industry category of each enterprise, the scale of each enterprise, and etc., and is coded according to predefined mapping tables. The second type of information is basically quantitative, including for example, almost all the variables on the balance sheet of each enterprise such as sales revenue, sales cost, total fixed assets, total assets, long term debt, total debt, total profit, total wages, and etc.

Table .7 gives the overview of the sample size information of the database. For example, the number of enterprises included in the database for year 2007 is 336,768, and the number of enterprises included in the database for year 2008 is 412,212. Because China's new Corporate Income Tax Law was passed in March 2007 and came into effect on January 1, 2008, we use the data for year 2006 as the pre-legislation observation, and use the data for year 2008 as the post-legislation observation.

Tables .3, .4, and .5 are the frequency tables for three categorical variables by year respectively: $Location \quad ID$, $Industry \quad ID$ and $EnterpriseScale$.

In order to fully understand the concept of *EnterpriseScale*, Table 6 gives the summary statistics of total employees and total assets by *EnterpriseScale* in 2003. By Table .2, a larger-size enterprise has on average more total employees and more total assets.

The type of registration (denoted as *RegistrationType*) of each enterprise tells us the type of each enterprise. Table .1 is the mapping table for the type of registration. Table .6 is the frequency table for the type of registration by year.

According to Table .1, we impute the value of as follows: (1) if *RegistrationType* of an enterprise is in ('110', '120', '130', '141', '142', '143', '149', '151', '159', '160', '171', '172', '173', '174', '190'), then we include the enterprise in the control group (i.e., DEs) and set the value of *treatment* for the enterprise to be zero; (2) Otherwise, we include the enterprise in the treatment group (i.e., FIEs) and set the value of *treatment* for the enterprise to be one.

## 2.6 Empirical Results

We start by checking whether the identifying assumption of our identification strategy is satisfied by plotting the trends of the mean of $log(Profit)$ of the treatment and control groups from year 2002 to year 2008. The graph is shown in .1.

.1shows two rising trends before year 2007 that are basically parallel to each other implying that there is little difference between the underlying trends in the pre-tax profit of the treatment and control groups so that the identifying assumption of our identification strategy is satisfied, and thus the difference-in-differences analysis conducted in Part (2) has solid foundation. .1 also shows that the two parallel trends diverge after year 2007, In particular, the control group keeps its original rising trend after 2007, while the treatment group switches to a slightly declining trend. This suggests that FIEs responded to the law by shifting their income out of China.

We first estimate 2.1 to examine FIEs' response to the. The regression results are reported in Column "Model 1" of .8. By Column "Model 1" of .8, one could reach four conclusions. First, as expected, the estimated coefficient of is positive at 0.002 and is statistically significant at the 1% level, which intuitively makes sense because an enterprise's profitability should have a positive impact on its profit. Second, as expected, an enterprise's scale of operations has a positive impact on its profit. Third, as expected, the estimated coefficient of is negative at $-1.406$ and is statistically significant at the 1% level, which intuitively makes sense because the 2008 global financial crisis should have a greater impact on enterprises with higher debt ratios. Finally, the estimated coefficient of the interaction term is negative at –0.346 and is statistically significant at the 1% level, which implies that FIEs are responding to the law by shifting their income out of China.

Then we estimate 2.2 to examine FIEs' response to the law by enterprise scale. The regression results are reported in Column "Model 2" of .8. By Column "Model 2" of .8, one could reach two new points. First, the estimated coefficients of $treatment \times postlegislation$, $treatment \times postlegislation \times DummyLargeSize$, and $treatment \times postlegislation \times DummyMediumSize$ are all negative at $-0.291$, $-0.326$, and $-0.220$ respectively and are all statistically significant at the 1% level. Second, the estimated coefficient of $treatment \times postlegislation \times DummyLargeSize$ is less than that of $treatment \times postlegislation \times DummyMediumSize$. These two new points are as expected and have two implications. First, they imply that FIEs of all sizes have responded to the law by shifting their income out of China. Second, they imply that the magnitude of the response is larger for larger-size enterprises, which intuitively makes sense because larger-size enterprises should have more capability of shifting income across countries.

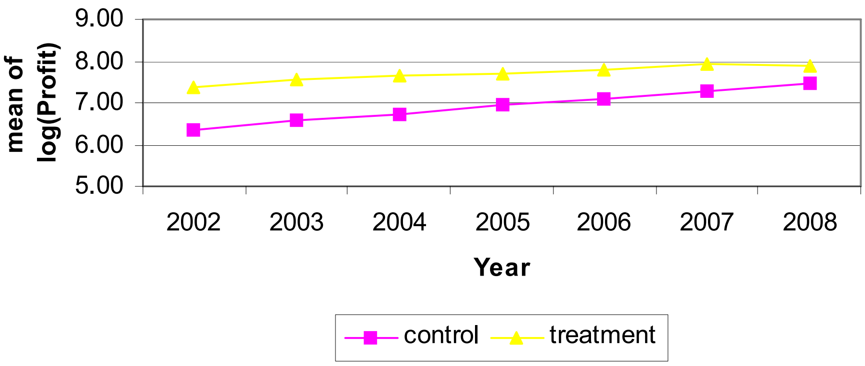
Finally, we estimate Equation (3) to examine whether FIEs from Hong Kong and Macau enterprises had a stronger response to the law in terms of income shifting. The regression results are reported in Column "Model 3" of .8. By Column "Model 3" of .8, one could reach another two new points. First, the estimated coefficient of $treatment \times postlegislation$ is negative at $-0.223$ and is statistically significant at the 1% level. Second, the estimated coefficient of $treatment \times postlegislation \times DummyHMT$ is negative at $-0.268$ and is statistically significant at the 1% level. These two new points also have two implications. First, they imply that FIEs responded to the law by shifting their income out of China. Second, they imply that the magnitude of the response is larger for HMT investment enterprises than that for other FIEs, which intuitively makes sense because both Hong Kong and Macau are tax havens (Dharmapala and Hines Jr. (2009)) so that the pre-tax profit of HMT investment enterprises should be more elastic than that of other FIEs.

The 2008 global financial crisis may have an impact on our estimates. Just like other countries, the 2008 global financial crisis had a serious impact on the Chinese economy and on Chinese domestic enterprises. Desai et al. (2008) show that MNCs have an advantage, namely, a superior ability to overcome financing constraints during a financial crisis, which implies that our results might underestimate the magnitude of the response of FIEs to the law. In order to address this concern, we have included DE as a control variable in our econometric models.

## 2.7 Conclusions

Since the early 1990s, China has maintained a dual corporate income tax regime, under which FIEs enjoyed certain preferential tax. China's new *Corporate Income Tax Law* that was passed in March 2007 terminated the dual corporate income tax regime by removing the tax preferences offered to FIEs by the Chinese government and unifying the income tax regime for FIEs and DEs. This paper uses a difference-in-differences approach to determine whether FIEs responded to the law by shifting their income out of China. We employ the Chinese Industrial Enterprises Database (2002-2008) to implement the analysis. We have three main findings. First, our estimates suggest that the law has driven FIEs to shift their income out of China. Second, the impact of the law is larger for larger-size enterprises, which might be due to their greater capability of shifting income across countries. Finally, we find that the impact of the law is larger for HMT investment enterprises than that for other FIEs, which is consistent with the fact that both Hong Kong and Macau are tax havens. All three findings are consistent with tax-induced income shifting.

Figure .1: The Trends of the Pre-Tax Profit of the Treatment and Control Groups (2002-2008)




Note: Profit is the pre-tax profit. Control group is the domestic enterprises. Treatment group is the foreign investment enterprises. Data is from the Chinese Industrial Enterprises Database from 2002 to 2008.

Table .1: The Mapping Table for the Type of Registration

| Level_1_Code | Level_2_Code | Level_3_Code | Type of Enterprise |
|---|---|---|---|
| 100 | | | Domestic Enterprises |
| | 110 | 110 | State-Owned Enterprises |
| | 120 | 120 | Collective-Owned Enterprises |
| | 130 | 130 | Share Cooperative Enterprises |
| | 140 | | Associated Enterprises |
| | | 141 | State-State Associated Enterprises |
| | | 142 | Collective-Collective Associated Enterprises |
| | | 143 | State-Collective Associated Enterprises |
| | | 149 | Other Associated Enterprises |
| | 150 | | Limited Liability Company |
| | | 151 | State-Owned Limited Liability Company |
| | | 159 | Other Limited Liability Company |
| | 160 | 160 | Limited Liability Stock Company |
| | 170 | | Private-Owned Enterprises |
| | | 171 | Private-Owned Company (only one owner) |
| | | 172 | Private-Owned Partnership Company |
| | | 173 | Private-Owned Limited Liability Company |
| | | 174 | Private-Owned Limited Liability Stock Company |
| | 190 | 190 | Other Enterprises |
| 200 | | | HongKong-Macau-Taiwan(HMT) Investment Enterprises |
| | | 210 | HMT-Mainland Joint Venture |
| | | 220 | Enterprise Jointly Managed by Mainland and HMT |
| | | 230 | HMT-Owned Enterprise |
| | | 240 | HMT-Owned Limited Liability Stock Company |
| 300 | | | Foreign Investment Enterprises |
| | | 310 | Chinese-Foreign Joint Venture |
| | | 320 | Enterprise Jointly Managed by China and Foreign Countries |
| | | 330 | Foreign-Owned Enterprise |
| | | 340 | Foreign-Owned Limited Liability Stock Company |

Note: Data is from the Chinese Industrial Enterprises Database from 2002 to 2008.

Table .2: The Distribution of Total Employees and Total Assets by EnterpriseScale

**Summary Statistics of Total Employees by Enterprise Scale**

| Category of EnterpriseScale | N | Mean | Median |
|---|---|---|---|
| "Large-Size" | 1,984 | 6,586 | 3,598 |
| "Medium-Size" | 21,647 | 886 | 648 |
| "Small-Size | 172,591 | 146 | 98 |

**Summary Statistics of Total Assets by Enterprise Scale**

| Category of EnterpriseScale | N | Mean | Median |
|---|---|---|---|
| "Large-Size" | 1,984 | 3,340,587 | 1,572,653 |
| "Medium-Size" | 21,647 | 271,883 | 134,954 |
| "Small-Size | 172,591 | 25,306 | 10,756 |

Note: Data is from the Chinese Industrial Enterprises Database from 2002 to 2008.

Table .3: The Frequency Table by Year for Location ID

| Location_ID | Area | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 |
|---|---|---|---|---|---|---|---|---|
| 11 | Beijing | 2.51 | 2.05 | 2.47 | 2.32 | 2.12 | 1.9 | 1.67 |
| 12 | Tianjin | 2.94 | 2.72 | 2.32 | 2.26 | 2.09 | 1.89 | 1.85 |
| 13 | Hebei | 4.2 | 4.04 | 3.35 | 3.66 | 3.52 | 3.23 | 2.95 |
| 14 | Shanxi | 1.91 | 1.84 | 1.82 | 1.63 | 1.55 | 1.33 | 1.03 |
| 15 | Neimeng | 0.79 | 0.84 | 0.82 | 0.9 | 1.02 | 1 | 0.89 |
| 21 | Liaoning | 3.31 | 3.49 | 4.11 | 4.23 | 4.89 | 4.92 | 5.12 |
| 22 | Jilin | 1.42 | 1.16 | 1.24 | 1.02 | 1.08 | 1.18 | 1.25 |
| 23 | Heilongjiang | 1.43 | 1.31 | 1.2 | 1.06 | 0.98 | 0.94 | 1.04 |
| 31 | Shanghai | 5.54 | 5.66 | 5.65 | 5.45 | 4.77 | 4.48 | 4.43 |
| 32 | Jiangsu | 11.83 | 12.16 | 14.65 | 11.85 | 12.03 | 12.42 | 15.42 |
| 33 | Zhejiang | 12.06 | 13.01 | 14.82 | 14.82 | 15.13 | 15.32 | 14 |
| 34 | Anhui | 2.16 | 2.12 | 1.72 | 1.94 | 2.16 | 2.41 | 2.69 |
| 35 | Fujian | 4.11 | 4.69 | 4.28 | 4.56 | 4.56 | 4.51 | 4.1 |
| 36 | Jiangxi | 1.69 | 1.55 | 1.53 | 1.62 | 1.77 | 1.79 | 1.63 |
| 37 | Shandong | 7.42 | 8.24 | 8.57 | 10.13 | 10.58 | 10.73 | 10.16 |
| 41 | Henan | 5.33 | 4.63 | 4.21 | 4 | 3.94 | 4.01 | 4.31 |
| 42 | Hubei | 3.41 | 3.2 | 2.28 | 2.51 | 2.5 | 2.67 | 2.85 |
| 43 | Hunan | 3 | 3.04 | 2.73 | 2.95 | 2.98 | 3.03 | 2.75 |
| 44 | Guangdong | 12.46 | 12.48 | 12.45 | 12.93 | 12.42 | 12.55 | 12.39 |
| 45 | Guangxi | 1.6 | 1.46 | 1.34 | 1.36 | 1.34 | 1.31 | 1.23 |
| 46 | Hainan | 0.33 | 0.32 | 0.23 | 0.23 | 0.2 | 0.14 | 0.13 |
| 50 | Chongqing | 1.13 | 1.14 | 0.95 | 1.08 | 1.06 | 1.16 | 1.45 |
| 51 | Sichuan | 2.7 | 2.78 | 2.67 | 2.93 | 2.98 | 3.18 | 3.21 |
| 52 | Guizhou | 1.14 | 1.08 | 0.91 | 0.95 | 0.86 | 0.68 | 0.61 |
| 53 | Yunnan | 1.14 | 1.02 | 0.86 | 0.87 | 0.86 | 0.8 | 0.73 |
| 54 | Tibet | 0.19 | 0.17 | 0.07 | 0.07 | 0.07 | 0.03 | 0.02 |
| 61 | Shaanxi | 1.36 | 1.27 | 1.12 | 1.1 | 1.12 | 1 | 0.89 |
| 62 | Gansu | 1.76 | 1.47 | 0.72 | 0.64 | 0.57 | 0.55 | 0.44 |
| 63 | Qinghai | 0.22 | 0.2 | 0.17 | 0.15 | 0.14 | 0.14 | 0.11 |
| 64 | Ningxia | 0.21 | 0.21 | 0.24 | 0.25 | 0.25 | 0.22 | 0.21 |
| 65 | Xinjiang | 0.7 | 0.64 | 0.52 | 0.53 | 0.49 | 0.47 | 0.44 |
| **Sum** | | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** |
| **Sample Size** | | **181,557** | **196,222** | **279,092** | **271,835** | **301,961** | **336,768** | **412,212** |

Note: Data is from the Chinese Industrial Enterprises Database from 2002 to 2008.

Table .4: The Frequency Table by Year for Industry ID

| Industry_ID | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 |
|---|---|---|---|---|---|---|---|
| 06 | 1.55 | 1.6 | 1.89 | 2.13 | 2.25 | 2.24 | 2.23 |
| 07 | 0.05 | 0.06 | 0.07 | 0.06 | 0.06 | 0.05 | 0.07 |
| 08 | 0.38 | 0.47 | 0.6 | 0.77 | 0.83 | 0.86 | 0.97 |
| 09 | 0.71 | 0.65 | 0.53 | 0.56 | 0.62 | 0.65 | |
| 10 | 0.94 | 0.93 | 0.79 | 0.82 | 0.86 | 0.89 | 0.96 |
| 11 | 0.01 | 0.01 | 0 | 0.01 | 0.01 | 0.01 | 0.01 |
| 12 | 0.21 | | | | | | |
| 13 | 5.74 | 5.7 | 5.17 | 5.36 | 5.42 | 5.39 | 5.53 |
| 14 | 2.54 | 2.36 | 2.03 | 2.04 | 2.01 | 1.97 | 1.97 |
| 15 | 1.81 | 1.63 | 1.27 | 1.29 | 1.3 | 1.31 | 1.31 |
| 16 | 0.16 | 0.13 | 0.08 | 0.07 | 0.06 | 0.04 | 0.04 |
| 17 | 7.3 | 7.57 | 8.72 | 8.3 | 8.39 | 8.29 | 8.04 |
| 18 | 4.99 | 4.95 | 4.33 | 4.36 | 4.33 | 4.39 | 4.42 |
| 19 | 2.17 | 2.3 | 2.3 | 2.29 | 2.27 | 2.21 | 2.09 |
| 20 | 1.67 | 1.78 | 1.82 | 1.99 | 2.11 | 2.33 | 2.5 |
| 21 | 0.97 | 1.04 | 1.09 | 1.13 | 1.19 | 1.22 | 1.31 |
| 22 | 2.91 | 2.84 | 2.7 | 2.74 | 2.61 | 2.49 | 2.43 |
| 23 | 2.1 | 2.08 | 1.87 | 1.78 | 1.67 | 1.51 | 1.57 |
| 24 | 1.28 | 1.28 | 1.21 | 1.24 | 1.2 | 1.21 | 1.16 |
| 25 | 0.63 | 0.67 | 0.73 | 0.73 | 0.72 | 0.64 | 0.58 |
| 26 | 6.96 | 7.03 | 6.78 | 6.89 | 6.86 | 6.82 | 6.85 |
| 27 | 2.03 | 2.07 | 1.71 | 1.83 | 1.78 | 1.71 | 1.58 |
| 28 | 0.5 | 0.48 | 0.55 | 0.48 | 0.46 | 0.46 | 0.49 |
| 29 | 1 | 1.03 | 1.15 | 1.12 | 1.11 | 1.1 | 1.13 |
| 30 | 4.22 | 4.27 | 4.42 | 4.43 | 4.47 | 4.57 | 4.73 |
| 31 | 8.43 | 8.28 | 7.24 | 7.4 | 7.26 | 7.21 | 7.4 |
| 32 | 1.84 | 2.1 | 2.58 | 2.45 | 2.32 | 2.13 | 1.94 |
| 33 | 1.62 | 1.72 | 1.91 | 1.9 | 1.94 | 1.99 | |
| 34 | 5.53 | 4.97 | 5.09 | 5.08 | 5.16 | 5.35 | 5.95 |
| 35 | 5.93 | 6.39 | 7.43 | 7.35 | 7.59 | 7.95 | 8.96 |
| 36 | 3.61 | 3.63 | 3.96 | 3.77 | 3.85 | 3.98 | 4.24 |
| 37 | 4.11 | 4.22 | 4.28 | 4.16 | 4.17 | 4.18 | 4.51 |
| 39 | 0.06 | 5.3 | 5.82 | 5.65 | 5.6 | 5.74 | 6.24 |
| 40 | 5.17 | 2.98 | 3.3 | 3.26 | 3.22 | 3.33 | 3.21 |
| 41 | 2.93 | 1.28 | 1.41 | 1.37 | 1.35 | 1.34 | 1.36 |
| 42 | 1.18 | 2.17 | 1.85 | 1.89 | 1.91 | 1.91 | 1.73 |
| 43 | 2.52 | 0.05 | 0.14 | 0.16 | 0.18 | 0.19 | 0.26 |
| 44 | 2.72 | 2.55 | 2 | 2.03 | 1.9 | 1.65 | 1.51 |
| 45 | 0.18 | 0.18 | 0.18 | 0.18 | 0.17 | 0.18 | 0.21 |
| 46 | 1.33 | 1.23 | 0.98 | 0.92 | 0.82 | 0.52 | 0.5 |
| **Sum** | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** |
| **Sample Size** | **181,557** | **196,222** | **279,092** | **271,835** | **301,961** | **336,768** | **412,212** |

Note: Data is from the Chinese Industrial Enterprises Database from 2002 to 2008.

Table .5: The Frequency Table by Year for EnterpriseScale

| EnterpriseScale | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 |
|---|---|---|---|---|---|---|---|
| Large-Size | 4.82 | 1.01 | 0 | 0.92 | 0.89 | 0.86 | 0.72 |
| Medium-Size | 8.03 | 11.03 | 0 | 10.03 | 10.02 | 9.98 | 8.66 |
| Small-Size | 87.15 | 87.96 | 0 | 89.05 | 89.09 | 89.16 | 90.62 |
| missing | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| **Sum** | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** |
| **SampleSize** | **181,557** | **196,222** | **279,092** | **271,835** | **301,961** | **336,768** | **412,212** |

Note: Data is from the Chinese Industrial Enterprises Database from 2002 to 2008.

Table .6: The Frequency Table by Year for Registration Type

| RegistrationType | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 |
|---|---|---|---|---|---|---|---|
| 110 | 16.22 | 11.84 | 9.14 | 6.19 | 4.82 | 2.99 | 2.25 |
| 120 | 15.13 | 11.46 | 6.5 | 5.86 | 4.7 | 3.87 | 2.7 |
| 130 | 5.61 | 4.73 | 2.95 | 2.75 | 2.09 | 1.75 | 1.32 |
| 141 | 0.18 | 0.15 | 0.1 | 0.08 | 0.06 | 0.05 | 0.03 |
| 142 | 0.3 | 0.25 | 0.14 | 0.12 | 0.11 | 0.09 | 0.06 |
| 143 | 0.4 | 0.28 | 0.15 | 0.13 | 0.1 | 0.08 | 0.05 |
| 149 | 0.2 | 0.18 | 0.12 | 0.11 | 0.09 | 0.08 | 0.05 |
| 151 | 0.74 | 0.68 | 0.52 | 0.48 | 0.44 | 0.39 | 0.3 |
| 159 | 11.64 | 12.88 | 14.3 | 14.96 | 15.15 | 15.44 | 14.29 |
| 160 | 3.3 | 3.22 | 2.58 | 2.65 | 2.39 | 2.31 | 2.19 |
| 171 | 9.45 | 10.96 | 9.52 | 10.35 | 11.25 | 11.74 | 13.18 |
| 172 | 1.97 | 2.31 | 2.17 | 2.36 | 2.42 | 2.39 | 2.39 |
| 173 | 14.43 | 19.67 | 29.44 | 30.93 | 33.85 | 36.33 | 40.23 |
| 174 | 1.23 | 1.52 | 1.69 | 1.91 | 2.07 | 2.12 | 2.02 |
| 190 | 0.19 | 0.22 | 0.14 | 0.39 | 0.3 | 0.34 | 0.53 |
| 210 | 4.86 | 4.64 | 3.84 | 3.64 | 3.38 | 3.24 | 2.67 |
| 220 | 1.19 | 1.03 | 0.67 | 0.62 | 0.54 | 0.5 | 0.33 |
| 230 | 4.6 | 5 | 5.58 | 5.76 | 5.64 | 5.64 | 5.28 |
| 240 | 0.12 | 0.12 | 0.11 | 0.11 | 0.1 | 0.1 | 0.14 |
| 310 | 4.43 | 4.49 | 4.65 | 4.65 | 4.39 | 4.3 | 3.82 |
| 320 | 0.54 | 0.56 | 0.62 | 0.61 | 0.5 | 0.46 | 0.34 |
| 330 | 3.15 | 3.72 | 4.94 | 5.22 | 5.48 | 5.63 | 5.67 |
| 340 | 0.1 | 0.11 | 0.13 | 0.13 | 0.13 | 0.15 | 0.16 |
| **Sum** | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** | **100%** |
| **Sample Size** | **181,557** | **196,222** | **279,092** | **271,835** | **301,961** | **336,768** | **412,212** |

Note: Data is from the Chinese Industrial Enterprises Database from 2002 to 2008.

Table .7: Overview of the Chinese Industrial Enterprises Database (2002-2008)

| Year | Sample Size |
|---|---|
| 2002 | 181,557 |
| 2003 | 196,222 |
| 2004 | 279,092 |
| 2005 | 271,835 |
| 2006 | 301,961 |
| 2007 | 336,768 |
| 2008 | 412,212 |

Note: Data is from the Chinese Industrial Enterprises Database from 2002 to 2008.

Table .8: RESULTS FOR DIFFERENCE-IN-DIFFERENCE REGRESSIONS (DEPENDENT VARIABLES: $log(Profit)$

| Independent Variable | | Model 1 | Model 2 | Model 3 |
|---|---|---|---|---|
| Intercept | | 6.895*** | 6.888*** | 6.891*** |
| | | (SE: 0.073) | (SE: 0.073) | (SE: 0.073) |
| AssetsReturn | | 0.002*** | 0.002*** | 0.002*** |
| | | (SE: 0.000) | (SE: 0.000) | (SE: 0.000) |
| EnterpriseScale | | | | |
| | "Large-Size" | 4.433*** | 4.490*** | 4.427*** |
| | | (SE: 0.033) | (SE: 0.036) | (SE: 0.033) |
| | "Medium-Size" | 2.078*** | 2.115*** | 2.078*** |
| | | (SE: 0.011) | (SE: 0.012) | (SE: 0.011) |
| | "Small-Size" | 0 | 0 | 0 |
| | | (SE: 0.000) | (SE: 0.000) | (SE: 0.000) |
| DebtRatio | | -1.406*** | -1.407*** | -1.405*** |
| | | (SE: 0.014) | (SE: 0.014) | (SE: 0.014) |
| treatment | | 0.734*** | 0.728*** | 0.732*** |
| | | (SE: 0.012) | (SE: 0.012) | (SE: 0.012) |
| postlegislation | | 0.521*** | 0.521*** | 0.521*** |
| | | (SE: 0.008) | (SE: 0.008) | (SE: 0.008) |
| (treatment*postlegislation) | | -0.346*** | -0.291*** | -0.223*** |
| | | (SE: 0.017) | (SE: 0.018) | (SE: 0.019) |
| (treatment*postlegislation*dummy_LargeSize) | | | -0.326*** | |
| | | | (SE: 0.083) | |
| (treatment*postlegislation*dummy_MediumSize) | | | -0.220*** | |
| | | | (SE: 0.029) | |
| (treatment*postlegislation*dummy_HMT) | | | | -0.268*** |
| | | | | (SE: 0.022) |

Note: * Statistically significant at the 10% level ** Statistically significant at the 5% level *** Statistically significant at the 1% level. The estimated coefficients of other control variables are omitted. The mean, median, and standard deviation of the dependent variable are 7.042, 7.056, 1.981 respectively. Data is from the Chinese Industrial Enterprises Database from 2002 to 2008. Profit is the pre-tax profit. Control group is the domestic enterprises. Treatment group is the foreign investment enterprises. $log(Profit)$ is the dependent for Model 1, 2 and 3. The regressors for Model 1 are $AssetReturn$, $EnterpriseScale$,$DebtRatio$,$Z$ (controls including location and industry), $treatment$, $postlegislation$ and an interaction $treatment \times postlegislation$. The regressors for Model 2 include $AssetReturn$, $EnterpriseScale$,$DebtRatio$,$Z$ (controls including location and industry), $treatment$, $postlegislation$ and interactions $treatment \times postlegislation$, $treatment \times postlegislation \times dummyLargeSize$ and $treatment \times postlegislation \times dummyMediumSize$. The regressor for Model 3 are $AssetReturn$, $EnterpriseScale$,$DebtRatio$,$Z$ (controls including location and industry), $treatment$, $postlegislation$ and interactions $treatment \times postlegislation$ and $treatment \times postlegislation \times DummyHMT$.

# Chapter 3

# FDI Spillovers and the Investment Climate

## 3.1 Introduction

This paper looks into the productivity enhancing effects of foreign firms on domestic firms (spillovers) from foreign direct investment (FDI). Such spillovers from FDI is has been a subject of debate in both the policy arena and academia for many years. Since the early 1990s private capital flows have exceeded official foreign assistance to developing countries and most of it is in the form of foreign direct investment. At the same time, governments in developing economies have made numerous policies to attract FDI in order to spur economic development. Those policies are based on the expectation that FDI could increase productivity in the economy. Such both directly through investment in a Greenfield venture or acquisition of a domestic firm and indirectly through positive productivity spillovers on other domestic firms. Whereas there is a great deal of evidence that foreign owned firms are more productive than domestic firms, the evidence on the FDI spillovers is mixed. This paper uses a firm-level panel data of European economies to increase our understanding as to when, where and under what conditions FDI has positive spillover effects on domestic firms, and hence could improve national welfare. In particular, the hypothesis of wether and how investment conditions could enhance FDI and FDI spillovers has been explored.

Studies have shown that one justifications of subsidizing incoming foreign investment is the externality in the form of productivity spillovers. Productivity spillovers refer to the increase in productivity due to the presence of foreign firms. In the case of such positive spillovers, multinationals do not fully internalize the value of these benefits and government policies to promote FDI improves economic welfare. We define horizontal spillovers as occurring when domestic firm productivity is positively affected by firms with foreign presence in the same sector, while vertical spillovers occur when domestic firms are affected by firms with foreign equity in the upstream (forward linkage) or downstream sectors (backward linkages).

The transfer of technology is considered as one form of externality. Such a technology transfer can occur through a number of channels such as the transfer of managerial practices, production methods, marketing techniques or any other knowledge embodied in a product or service. For example, local firms may learn to imitate a new process or improve the quality of their product through observation, interaction with foreign managers, and from employees of foreign multinational corporations. Local firms may also benefit from the entry of new professional services or suppliers as a result of such multinations' entry. Foreign firms may act to catalyze domestic suppliers to improve the quality or efficiency of their good or service by demanding higher standards. On the other hand, foreign firms may have a negative effect on domestic firms' output and productivity, especially in the short run, if they compete with domestic firms for their market share or their best human capital. As domestic firms cut back production they may experience a higher average cost and higher unemployment, which may lower the overall economic welfare.

This paper explores futher the implications for policies toward FDI. There have been many FDI policies regarding FDI but they differ tremendously. Results from this study shed some light on the question which FDI policies best promote host countries' development; for instance, whether host country's productivity is boosted most by requiring host countries to share technology with domestic firms, or by allowing foreign firms to access all domestic industries, or by providing special treatment to lure foreign investors to choose the host country as a base for operations?

A new and unique dataset from the World Bank, *Investing Across Borders*, allows us to be the first work to test these hypotheses with a rich information of FDI policies. This data is a cross-country set of indicators that records and scores each countries' FDI specific investment environment. Using such a comprehensive data plus a cross-country firm-level panel, this study contributes to the literature by providing evidence of the effectiveness of these FDI policies.

## 3.2 Literature Overview

A number of papers test for productivity spillovers for domestic firms from foreign direct investment. In this sections extensive evidence of FDI spillovers will be reviewed. The earlier literature on FDI spillovers generally explore how foreign presence brings productivity externality in the same industry (horizontal spillovers), while more recent literature shows evidence on productivity externalities in the upstream or downstream industries (vertical spillovers).

Studies for horizontal spillovers use firm panel data to study whether the productivity of the domestic firms is correlated with the extent of foreign presence in the same sector. Research by Haddad and Harrison (1993) on Morocco, Aitken and Harrison (1999) on Venezuela, Djankov and Hoekman (2000) on the Czech republic, Konings (2000) in Bulgaria, Romania, and Poland has failed to find positive horizontal spillovers to domestic firms. The results cast doubts on such gains from FDI. However, evidences are found that positive horizontal spillovers are present in industrial countries. Haskel et al. (2007)'s estimated a robust and significant 0.5% increase in the domestic plants' TFP given a 10% increase in the same industry's foreign presence in UK. Using data in the United States from 1987-1996, Keller and Yeaple (2009) find large FDI spillovers that accounts for 14% of growth in productivity growth for US firms.

Such pattern for horizontal spillovers is argued to be an outcome due to the capability of the domestic firms to improve productivity from technology transfers. The negative spillover effect found in the less developed countries is argued to the result of low level of technology transfers to the domestic firms. There is also a hypothesis explaining the evidence that positive spillovers are found in more technologically advanced sectors or in the more industrialized countries, for instance UK and US. It is argued that the larger the technology or human capital gap between the domestic and foreign firms, the less likely the domestic firms will benefit from FDI. By using a variable of the share of the population with high school or higher education as a proxy of human capital, Borensztein et al. (1998) show that FDI is an important vehicle for the transfer of technology and economic growth, but only in countries which have human capital stock above a minimum threshold. Their study uses data on FDI flows from industrial countries of 69 developing countries. Blalock and Gertler (2004) have found that plants with more highly educated employees benefit more from the presence of multinational firms using firm-level data in Indonesia.

A recent stream in the literature argues that FDI is more likely to have positive productivity spillovers on the host country if the economy is open. Moran et al. (2005) found evidence using measures of openness by trade, FDI and competitiveness. In contrast, FDI is likely to worsen economic welfare of the host country in protected and distorted economies. Moran et al. (2005) have stated that "Foreign investors in countries with domestic content, joint venture and technology sharing requirements deploy production technique lagging far behind the frontier in international industry. Foreign affiliates with older technology and less efficient plants are not good candidates to develop from an infant industry to a robust world competitor. Local firms that sell to foreign affiliates in protected market are often subscale in size and inefficient in operation..."

By using Indian data, Aghion et al. (2005) showed that firms with higher technology are more likely to respond to liberalization by investing in new technologies. Blalock and Gertler (2005) used Indonesian data to show that sectors with more competition have higher spillovers. However, Sembenelli and Siotis (2005) found that only firms in R&D sector have this positive correlation between competition and spillovers, using Spanish data. Therefore, heterogeneous spillover effects may be caused by different level of liberalization and competition. This means that foreign affiliates tend to have more spillovers due to its better business environment.

While there are numerous studies on horizontal (intra-industry) spillovers, there are relatively few empirical studies on vertical spillovers. Moreover, vertical spillovers are more likely to be positive than horizontal spillovers since multinational companies have an incentive to improve the productivity of their suppliers but not their competitors. The few empirical papers find evidence that is consistent with of technology transfer through backward linkages in the manufacturing sectors. In their seminal work, Javorcik (2004) and Blalock and Gertler (2008), using firm-level data from Lithuania and Indonesia respectively, find that the FDI spillovers are more likely to be vertical than horizontal. They argue that because multinationals firms have incentive to prevent information or technology leakage to its domestic competitors, the magnitude of horizontal spillovers tend to be very small, if any. At the same time, multinationals may transfer knowledge or skill to their domestic suppliers to enhance their performance. They found supporting evidence for such backward linkages. However, these studies rely only on a variable that is constructed from input-output tables at the industry level, rather than a direct firm-specific variable.

Research in institutional economics stressed the importance of institution on a country's long-run development (Glaeser and Shleifer (2002), Acemoglu et al. (2001), etc.). A number of research find out that laws, regulations, contract enforceability are important determinants for government and economic performance. Djankov et al. (2002) studies data of number of procedures and time to start a new business that a start-up as costs of entry. They find that countries with heavier regulation of entry have higher corruption and larger unofficial economies, but not better quality of public or private goods. Countries with more democratic and limited governments have lighter regulation of entry. This paper studies the impact of a range of institutional features (local restrictions, law and regulation, contract enforceability, etc.) on the direction and the magnitude of spillovers from FDI.

Research has provided both theoretical framework and empirical evidence that business environment affects spillovers. First, firms in the sectors with more competition may have greater FDI spillovers (Blalock and Gertler (2008) and Abraham et al. (2010)). Liberalization may lead to higher spillovers (Aghion et al. (2005)). They developed a simple Schumpeterian growth model to understand how firms respond to entry threat imposed by such liberalization. They show that firms in pro-business institutions are more likely to invest in new technologies and production processes, in response to foreign entry threat. They use Indian data in the period of liberization (industrial delicensing) to empirically support their theory. Therefore, the first conclusion is that firms in an open and competitive environment will have greater spillovers. In addition, better business environment also results in more advanced technology.

Second, imposing FDI or trade restrictions may not serve to promote host country's economic development. Some developing countries have adopted policy measures such as domestic equity requirements, joint venture mandates and technology sharing regulations. Moran et al. (2005) have shown that "intrafirm trade" and "parental supervision" of multinational corporations are potent channel for host country's productivity growth. Restrictive FDI policies are most likely to interrupt those channels of development and decrease the willingness of foreign companies to share their technology. Their book shows more striking evidence in restrictive economies, FDI is likely to worsen the host country's economic welfare: "If FDI is motivate by the desire to service a protected and distorted domestic market,…Foreign firms may find it profitable to operate, but they may do so without bringing the best technologies and/or using the country as part of their international supply network. By contrast, impact will likely be positive when FDI is motivated by the desire to participate fully in the international sourcing networks of the parent multinational, and operations are unrestricted by rules on ownership and local content." It is also supported by the evidence that unsuccessful FDI policies in Africa stems from those distorted and protected economies while China's success results from its openness and the multinational's intentions of increasing global integration. Thus, business environment will affect the quality of FDI and its spillovers. Poor business environment could lead to outdated technology and inefficient production processes.

Third, information transparency and credibility are also known to strengthen FDI gains. Government of the host country trying to attract foreign direct investment would face the information asymmetry problem (Akerlof (1970)). Unlike used car sellers, however, host governments cannot offer warranties to reduce risks, but they could address this problem by providing transparent and up-to-date information regarding foreign investment. Rodrik and Hausmann (2004) argue that providing up-to-data information for the feasibility of foreign investment leads to information externality. A World Bank FIAS (Foreign Investment Advisory Service) report by Wells and Wint (2000) shows reducing entry costs increases the social returns: Fours dollars of estimated returns for every dollar spent. And such entry costs include the search cost for foreign direct investors, credibility of information, and facilitating site comparison etc.

Four, strength of laws and protection of property rights are also known to affect FDI. Aizenman and Spiegel (2006) used a principal-agent framework where ex-post monitoring of contracts is more costly for foreign investors than for domestic ones to argue that the share of FDI in total investment should be lower in countries with weak enforcement of property-rights. Kaufmann et al. (1999) shows evidence that regulatory burden and rule of law correlates significantly with FDI, using a wide range of institution variables. La Porta et al. (1998) used the International Country Risk Guide to show that the risk of repudiation of contracts by government, risk of expropriation and shareholder rights do matter. Moreover, the investment environment tend to impact FDI spillovers through various channels. Gorodnichenko et al. (2007) is one of the first paper to shed light on the impact of a country's institutions, especially corruption and bureaucratic red tape, and the level of development on the strength of vertical and horizontal spillovers. They find positive backward spillovers for the domestically owned firms raises a domestic firm's efficiency. Their estimation also suggests that buying inputs from or competing with foreign firms confers positive spillovers only for firms in the service sector. In addition, they found no evidence for the institution environment could hence spillovers effects. Regarding its ownership relationship with spillovers, Javorcik and Saggi (2010) found that firms' ownership structures may be correlated with the quality of FDI. For those foreign affiliates with more advanced technology, the ownership tends to be full than joint-venture to protect their technology. Thus, such firms tend to have greater spillovers.

## 3.3 Data

In this study I use a large European panel which cover the firm-level information from year 2005 to 2008. This database is a standardized commercial data called Amadeus collected by about 50 vendors across Europe. There are two main database, the financial database and the ownership data. These two dataset are provided by the vendor separately. The financial data records over 10 million firms' basic financial statements, which covers the business profiles, the balancesheet information, the cash flow/profit information and key ratios of both public and private companies across 41 European countries. The ownership data contain the ownership/shareholder information. In particular, it identifies the shareholders' country of origin and the percentage of its ownership. In this study I use a subsample of the firms with non-missing ownership information. For my research it is important to identify foreign firms for each country each year. But I do not observe a firm's foreign investment directly in this dataset. In order to identify which FDI from this firm level data, I use the ownership information from the European panel to extrapolate such information. This database provides information on firm ownership, with information of its major shareholders. Based on such ownership information and the total asset value, the foreign asset holdings for each company is calculated for each year. The value of firm-level foreign direct investment (FDI) in year t is the difference in value between foreign asset holdings at year t and year t-1. Following Gorodnichenko et al. (2007), my sample covers both the manufacturing and the service sectors, excluding only the utility and financial firms. More firms are analyzed in the paper while earlier research focuses on the manufacturing industries only.

To study how investment climate impact the strength of FDI spillovers, this paper utilizes the *Investing Across Borders* (IAB) indicators. The Investment Climate Advisory Services of the World Bank Group constructed the indicators in July 2010. They measure FDI regulation across 87 economies. The indicators measure openness to FDI through equity ownership permitted in various sectors (11 indicators), ease of starting a foreign business (3 indicators including the time spent and procedure to go through staring business), arbitrating commercial disputes (3 indicators which measure how well court systems develop), and accessing industrial land (6 indicators that scores land availability). In this study all the above indicators are used to test the validity of hypotheses based on different sets of investment condition measures. The data are compiled from detailed surveys filled out by over 2,300 respondents all over the world. In terms of the coverage of topics, sectors, and countries, this dataset on FDI regulations is the most comprehensive to date (Wagle (2010)).

Table .2 shows the summary statistics for the whole sample. Columns 1 to 6 lists summary statistics for key variables (sales, capital, labor, material costs; horizontal, forward and backward linkages) for six European countries—Bulgaria, Czech Republic, France, Poland, Romania and Spain. The selection of such a sample is based on the availability of key variables, ownership data and input-ouput tables. This is a firm-level database which contains over half a million observations. But the quality of the data varies across countries: Spain has the best data, which covers over half of the whole sample. France has the second largest share contributing over 20% of the sample. As the table shows, there is also variation of key variables across countries. French firms seem to have much lower value for all variables. There is also large dispersions for horizontal linkage and forward linkage.

The original sample of IAB indicators contains 87 countries and the European database consists of company information for 41 European countries. However, the available Input-Output tables restrict our samples to ten European countries. Within the sample of these ten countries, four countries have most of their financial information missing, which disqualify the extracted sample for economic analysis. For the rest of the countries, the final sample for analysis also shrinks significantly from the original sample.

The IAB indicators are divided to four categories to reflect various aspect of a country's investment climate: Investing Across Sectors indicators, Starting A Foreign Business indicators, Accessing Industrial Land indicators and Arbitrating Commercial Disputes indicators. 1. The Investing Across Sectors indicators measure the maximum percentage of ownership allowed across 33 subsectors. In this paper, I construct a country-level ownership indicator by averaging all the sector-specific ownership within a country. The higher the indicator, the more open a country is towards foreign direct investment. 2. Starting A Foreign Business indicators consist of three major indicators that measures the easiness of a foreign company for starting a business in the host country. The Ease of Establishment indicator scores the overall environment foreign companies face to set up a business. Higher scores mean less difference in treating domestic and foreign business for business establishment. The Number of Procedures indicator records the official procedures required to start a business, both pre- and post- incorporation. The Time in Days indicator is the days taken to comply with all the official requirement to start a business. 3. The Access Industrial Land indicator measures the easiness of land access for foreign business. The Time to Lease Public Land indicator shows the days taken to lease land from the government. The Time to lease Private Land indicator shows the days taken to lease land from a private owner. The Availability of Land Information index is constructed based on the availability of 18 pieces of information regarding land plots. The Access to Land information index measures the easiness of a foreign business to obtain land information, based on how well a country's land registry maintains and shares land data. The Strength of Lease Rights index analyzes the degree of restrictions a foreign-owned company face to lease land. The Strength of Ownership Rights Index measures the restriction in terms of purchasing land by a foreign business. 4. The Arbitrating Commercial Disputes indicators capture the important legal aspect of a country's investment climate. The Strength of Law index scores a country's overall legal framework for dispute resolution. The Ease of Arbitration Process index captures the degree of restrictions and obstacles a foreign company faces in seeking a dispute resolution. The Extend of Judicial Assistance Index measures the effectiveness of interactions between arbitral tribunals and domestic courts.

Table .3 shows the summary statistics of the IAB indicators. The first two columns show the mean and standard deviations for each indicator for the six country in my sample. It is easily observed that there is no variation across these countries for the variable Strength of

Ownership Rights. In fact, all six countries have scores of 100 for this variables. Therefore, there would not be any information derived from this variable, thus it is excluded for further analysis. The observations of most of the indicators are on a scale of 100, except for the procedure and time to start foreign business, time to lease public and private land. The rest of the columns show the correlations among all indicators. These correlations show the necessities of constructing various indicators of investment climate. They help us to understand a country's investment climate in different aspects. Not all the indicators are positively correlated, meaning that investment climate measures are not all consistent. For example, a good investment climate defined by Average Ownership may well be measured as bad using Strength of Leaser Rights indicator, due to the very negative correlation (-83%) between the two indicators.

## 3.4 Methodology

To examine the relationship between domestic firms' productivity and FDI in the same industry or other industry, I apply the approach used by early literature (Javorcik (2004), Gorodnichenko, Svejnar and Terrell (2007), Du, Harrison and Jefferson (2011)) that is characterized by the following equation for estimation.

$$\begin{aligned} lnY_{i,j,k,t} = {} & \alpha + \beta_1 lnK_{i,j,k,t} + \beta_2 lnL_{i,j,k,t} + \beta_3 lnM_{i,j,k,t} \\ & + \beta_4 ForeignShare_{i,j,k,t} + \beta_5 Horizontal_{j,t} + \beta_6 Backward_{j,t} + \beta_7 Forward_{j,t} \\ & + \beta_8 Horizontal_{j,t} \cdot IAB_k + \beta_9 Backward_{j,t} \cdot IAB_k + \beta_{10} Forward_{j,t} \cdot IAB_k \\ & + \tau_t + \eta_j + \psi_k + \varepsilon_{i,j,k,t} \end{aligned}$$

$Y_{i,j,k,t}$ stands for the real output from firm $i$ operating in sector $j$ and country $k$ at time $t$. Labor is the number of employees. $M_{i,j,k,t}$ is the firm's material cost. $ForeignShare_{i,j,k,t}$ shows what the proportion it is for foreign investors.

$Horizontal_{j,t}$ is constructed to capture the extent of foreign presence in sector $j$ at time $t$. It is defined as the foreign ownership averaged over all firms in one sector:

$$Horizontal_{j,t} = \frac{\sum_{i \in j} ForeignShare_{i,t} \cdot Y_{i,t}}{\sum_{i \in j} Y_{i,t}}$$

This variable measures the of share of foreign output in one industry. The same measure is adopted in Javorcik (2004) to capture the industry's foreign presence. The larger this variable is, the more foreign equity or more foreign output for one industry. $Backward_{j,t}$ proxies for the foreign presence in the downstream industries of sector $j$—industries that are supplied by industry $j$. Such a variable captures the relationship between domestic suppliers and foreign customers.

$$Backward_{j,t} = \sum_{h \neq j} \alpha_{j,h} \cdot Horizontal_{h,t}$$

$\alpha_{j,h}$ denotes the share of sector $j$'s output supplied to sector $h$, taken from Input-Output table at the two-digit NACE level. NACE is the standard industry classification for European companies. The exact firm-level information of upstream-downstream relationship would be ideal for this study. Since such detailed information is not available and the best information of upstream-downstream relationship can be obtained is industry level, industry level measure of downstream foreign presence is proxied using industry-level information. Here inputs supplied within the same sector are excluded, since any effect would already be calculated in the Horizontal variable. The greater the foreign presence in the downstream industries, the higher the value of this. $Forward_{j,t}$ captures the foreign presence in sector $j$'s upstream industries—industries that supply industry $j$:

$$Forward_{j,t} = \sum_{m \neq j} \beta_{j,m} \cdot Horizontal_{m,t}$$

Here $\beta_{j,m}$ is the proportion of inputs purchased by $j$ from sector $m$. Similar to $Backward_{j,t}$, the greater the foreign presence the upstream the higher this value is. Such construction makes all these variables both sector-specific and time-varying. Table 2 shows the Input-Output tables to use for the sample countries from 2005 to 2008. Because the input-output relationship between sectors may change overtime, using year-specific input-output matrices would be ideal. Unfortunately, it shows that not all the tables are available for every year. In fact, most of the IO tables are not available. For those years where tables are unavailable, available tables that are in closest years are used instead. For example, since the 2008 IO table is not available for Czech Republic, the table for 2007 is used instead. This methodology is also applied in other FDI spillover literature such as Javorcik (2004).

Table .3 shows the summary statistics of key variables for the six countries included in my sample. French firms seem to be distinctive in terms of the mean of log sales, capital, foreign shares, as well as spillover variables (horizontal, forward and backward linkages). Value from all other countries are in similar magnitudes. Spanish companies cover more than half of the entire sample (368,609 out of 671,961 observations) and the smallest sample comes from Czech Republic (5,547 observations). Therefore, power of country-specific statistical estimation will depend on the sample size of each country. The smaller the sample size, the weaker the econometric tests.

Table .4-.9 shows the time-varying measures of horizontal, forward and backward linkages for each country. One can observe that those measure could change dramatically within one year, such as for Bulgaria, but not much so for countries like Poland. There are a few econometric issues in the analysis. There could be firm-specific, region-specific or country-specific omitted variable bias. This may bias the relationship between productivity and foreign presence. I will use time-differencing and control for the year, region, industry and firm fixed effects.

$$\begin{aligned}\triangle lnY_{i,j,k,t} = {} & \beta_1 \triangle lnK_{i,j,k,t} + \beta_2 \triangle lnL_{i,j,k,t} + \beta_3 \triangle lnM_{i,j,k,t} + \beta_4 \triangle ForeignShare_{i,j,k,t} \\ & + \beta_5 \triangle Horizontal_{j,t} + \beta_6 \triangle Backward_{j,t} + \beta_7 \triangle Forward_{j,t} \\ & + \beta_8 \triangle Horizontal_{j,t} \cdot IAB_k + \beta_9 \triangle Backward_{j,t} \cdot IAB_k + \beta_{10} \triangle Forward_{j,t} \cdot IAB_k \\ & + \tau_t + \eta_j + \psi_k + \varepsilon_{i,j,k,t}\end{aligned}$$

The above specification reduces the noise in estimation and gives more weight to persistent changes in the variables of interest. However, differencing on the data means a reduction of sample size. Taking longer lags makes the sample even smaller. If estimated by OLS, this analysis has some identification limitations. Griliches and Mairesse (1995) argues that OLS treats labor and other inputs as exogenous variable, but they should be endogenously determined based on productivity. Treating those inputs as exogenous will bias the results. Olley and Pakes (1996) used a semiparametric estimation to allow for idiosyncratic firm productivity over time. They assume that firms choose their desired capital stock and other input variables in the beginning of every period:

$$k_{i,t+1} = (1-\delta)k_{i,t} + i_{i,t}$$

I take logs of the Cobb-Douglas production function:

$$lnY_{i,t} = \alpha + \beta_l lnL_{i,t} + \beta_k lnK_{i,t} + \beta_m lnM_{i,t} + \omega_{i,t} + \eta_{i,t}$$

$\omega_{i,t}$ is productivity and $\eta_{i,t}$ denotes random error. Both of them are unobserved; the difference between the two is that $\omega_{i,t}$ is a state variable in firm's decision problem, hence a determinant of factor inputs ($L_{i,t}$, $K_{i,t}$, $M_{i,t}$). But $\eta_{i,t}$ does not correlate with inputs. Estimation of the above model would yield biased results, because inputs are determined based on the firm's expectation of $\omega_{i,t}$. And if there is serial correlation in $\omega_{i,t}$, current period inputs will be positively correlated with it; in this case, an OLS procedure is likely to yield results with coefficients on inputs biased upwards. Since investment is a function of capital stock and firm productivity:

$$i_{i,t} = i_{i,t}(\omega_{i,t}, k_{i,t})$$

Because the investment function if strictly monotonic in productivity, one can invert the above equation to write the unobservable $\omega_{i,t}$ as a function of the observables:

$$\omega_{i,t} = h_{i,t}(i_{i,k}, k_{i,t})$$

The above equation allows us to write the unobservable productivity variable $\omega_{i,t}$ as a function of observables. Such a formulation enable me to control for productivity in estimations. Olley and Pakes (1996) make two assumptions: First, there is only one unobservable in the above equation. Second, investment is an increasing function of productivity. Although they are strong assumptions, Olley and Pakes (1996) argue these assumptions yield two advantages: They give rise to a simple estimation algorithm for production function parameters without relying on more assumptions necessary to fully specify equilibrium. These assumptions also generate an overidentified model and allows me to directly test these assumptions.

Substituting the above equation into the Cobb-Douglas function. Now the equation becomes:

$$\begin{aligned} y_{i,t} &= \alpha + \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_m m_{i,t} + h_{i,t}(i_{i,t}, k_{i,t}) + \eta_{i,t} \\ &= \alpha + \beta_l l_{i,t} + \beta_k k_{i,t} + \phi_{i,t}(i_{i,t}, k_{i,t}) + \eta_{i,t} \end{aligned}$$

Where $y_{i,t}$, $l_{i,t}$, $k_{i,t}$, $m_{i,t}$ denote the logarithm value of $L_{i,t}$, $K_{i,t}$, $M_{i,t}$. In the first stage of estimation, the consistent estimates of coefficients on labor, materials and the form of a non-parametric term $\phi_{i,t}$ will be obtained. But $\beta_k$ can not be estimated consistently in this stage. The second step identifies the coefficient for capital by using a non-linear least squares.

$$y_{i,t} - \beta_l l_{i,t} - \beta_m m_{i,t} = \phi_{i,t}(i_{i,t}, k_{i,t}) + \varepsilon_{i,t}$$

The above equation highlights the needs for the first stage of estimation of $\phi_{i,t}(i_{i,t}, k_{i,t})$. Since $\phi_{i,t}$ is mean independent of variables pre-determined at the beginning of period $t$, $\phi_{i,t}(i_{i,t}, k_{i,t})$ is mean independent of the pre-determined state variable $k_{i,t}$. However, labor decision $l_{i,t}$ is a function of $\phi_{i,t}$. Such correlation calls for the first stage estimation. For simplicity, $\phi_{i,t}(i_{i,t}, k_{i,t})$ is estimated by a series of polynomials. The second stage substitute the estimated $\phi_{i,t}$ into the formula and run non-linear least squares for the Cobb-Douglas equation.

There are two important assumptions with this estimation procedure. One is the first-order Markov assumption of productivity $\omega_{i,t}$, and the timing assumption about capital accumulation. The first-order Markov assumption decomposes it into its conditional expectation at time $t-1$, $\mathbb{E}(\omega_{i,t}|\omega_{i,t-1})$ and a deviation from that expectation, $\omega_{i,t} - \mathbb{E}(\omega_{i,t}|\omega_{i,t-1})$, which is the innovation of the productivity. These two assumptions allow it to construct an orthogonal relationship between capital and the innovation component in productivity, which is used to identify the coefficient on capital. However, one disadvantage of applying the Olley-Pakes procedure is that many firms report zero or negative investment. To address this problem, I also explore the robustness of the results to using the Levinsohn and Petrin (2000) approach. With the Olley-Pakes correction, I can get an unbiased estimate of the firm's productivity. Therefore, I could derive the total factor productivity (TFP) instead of the log of output, which is the difference between the actual and predicted output:

$$tfp_{i,t} = y_{i,t} - \beta_l l_{i,t} - \beta_m m_{i,t} - \beta_k k_{i,t}$$

Specifically, this is a two-stage estimation procedure when using TFP as the dependent variable. The first step follows Olley-Pakes procedure to obtain unbiased coefficients on input variables and then calculate TFP (residual from the production function). The second step is to regress TFP on firm-level controls and FDI variables.

## 3.5 Estimation

### Estimation of FDI Spillovers

This section shows how investment environment, in particular the FDI-related policies, could impact productivity spillovers. There has been a recent strand of literature that explore the relationship between countries' institutional features and FDI spillovers. Moran et al. (2005) shows evidence that countries that are more open trade and FDI policies enjoy more benefits from FDI. For countires with more protective regulations, FDI could have negative impact on the productivity of the host country. Using a sample of European companies, I first test the traditional hypothesis on the channels of FDI spillovers—the forward, backward and horizontal linkages related the specification below:

$$\begin{aligned} lnY_{i,j,k,t} = {} & \alpha + \beta_1 lnK_{i,j,k,t} + \beta_2 lnL_{i,j,k,t} + \beta_3 lnM_{i,j,k,t} + \beta_4 ForeignShare_{i,j,k,t} \\ & + \beta_5 Horizontal_{j,t} + \beta_6 Backward_{j,t} + \beta_7 Forward_{j,t} \\ & + \tau_t + \eta_j + \psi_k + \varepsilon_{i,j,k,t} \end{aligned}$$

I use the baseline OLS and two-stage OLS to estimate the above model. The two-stage OLS follows the usual treatment in the literature: I first obtained the TFP residual from the first step regressions and the second step regressions produce the coefficients of interests for channels of FDI spillovers.

Table .10 shows results from the ordinary least squares for six countries. Column 1-6 shows baseline OLS results for each country and Column 7 shows results using the entire sample. There has been a drop in observations for all countries, due to the missing observation of differencing each variable. Not surprisingly, most coefficients on production factors (labor, capital, material) are positive and significant. There is not much effect of foreign share on the company's sales. The most important analysis is for the spillover effect. The table shows significant and positive spillovers effect via backward linkages for Romania, Spain and the whole sample. This results is consistent with the finding in the recent literature that FDI improves economic productivity by enhancing the performance of upstream companies. However, this coefficient for France is the opposite. For France and the whole sample, spillover tend to impact productivity negatively through horizontal linkages. This is likely due to the fact the entering of a more competitive foreign business reduces not only the incumbents' but also the overall sales in the same industry. And there seems to be some negative effects of forward linkages measures.

Table .11 provides a slight alternative empirical model to the OLS–the two-stage OLS model. The upper panel shows the first stage regression results, while the lower panel shows the second stage results. In the first stage, log sales are regressed on production facts and the residual are derived as the total factor productivity (TFP). All the coefficients in the first stage are significant and R-square vary from 20% to around 50%. which accounts for time-invariant unobservable characteristics. The R-squares for the second stage is quite small (all of them are less than 1%). This low R-square is partly because variables for spillover channels are industry-level measures thus less explanatory power. The two stage OLS results are very similar to the baseline OLS results. Backwards linkage could be observed for the whole sample, but not for individual countries. The backward linkage seems to contribute positively to productivity, which is consistent with previous research. However, for each individual country, the effect diminishes—there is no significant backward linkage effect for Bulgaria, Czech Republic and Poland, and French data even shows negative signs.

These baseline results confirm the previous finding of the recent research that FDI improves productivity via backward linkages. However, results seem to be noisy for individual countries. And because spillover variables (horizontal, backward, forward) are country-specific measures. Their interactions with IAB ownership data would be correlated with themselves, generating a collinearity problem. Therefore I will use the whole sample for further analysis for investment climate's productivity enhancing effect.

## Estimation of the Investment Climate

This study future explores how FDI environment could impact the productivity spillovers from FDI. The World Bank's *Investing Across Borders* indicators are used to quantify a country's openness to the foreign direct investment. These indicators cover various aspects of a country's investment climate: foreign ownership index, easiness of starting a foreign business, foreign access to land and easiness of arbitrating commercial disputes.

In this section, the impact of each indicator on FDI spillover is tested and examined in data. Recent research has shown some evidence that investment environment may affect FDI spillovers. A more competitive and open environment may enable domestic firms to better absorb productivity gains from foreign investment. Such empirical exercises have important implications for a country's development of investment environment. Moran et al. (2005) argue that in market with worse investment environment, foreign firms' suppliers are sub-optimal in terms of size and operation efficiency. Blalock and Gertler (2008) and Abraham et al. (2010) find empirical support that positive spillover effect happens in industries that are less restrictive and more competitive.

All four sets of Investing Across Borders indicators reflect a country's openness to foreign investments, however they measure quite different aspects of investment environment. Foreign ownership indices measure the maximum of foreign ownership allowed across the main sectors. Coefficients on the interactions of horizontal, backward and forward measures the incremental productivity contribution of FDI environment via the horizontal linkage, backward linkage and forward linkage, respectively.

$$\begin{aligned} lnY_{i,j,k,t} = {} & \alpha + \beta_1 lnK_{i,j,k,t} + \beta_2 lnL_{i,j,k,t} + \beta_3 lnM_{i,j,k,t} \\ & + \beta_4 ForeignShare_{i,j,k,t} + \beta_5 Horizontal_{j,t} + \beta_6 Backward_{j,t} + \beta_7 Forward_{j,t} \\ & + \beta_8 Horizontal_{j,t} \cdot IAB_k + \beta_9 Backward_{j,t} \cdot IAB_k + \beta_{10} Forward_{j,t} \cdot IAB_k \\ & + \tau_t + \eta_j + \psi_k + \varepsilon_{i,j,k,t} \end{aligned}$$

Table .12 shows the results from the above specification using IAB's variable on the average ownership limit across industries. Each column shows results from one econometric specification: Baseline OLS, Two Stage OLS, and Olley-Pakes. Olley Pakes method is used to correct for the simultaneous choice problem. The first stage of the two stage Olley-Pakes is using the Olley-Pakes model to derive the total factor productivity (TFP). The second stage is to estimate the effects of other variables on TFP. Across all specifications, the coefficients on production factors are positive and significant. The foreign share is likely to affect productivity only in the Olley-Pakes specification. In these estimations, FDI tends to have a negative effect on productivity via backward linkages, with exception for the Olley-Pakes model. The ownership limit seems to directly influence productivity in a positive way, which implies that the higher the foreign ownership is allowed, the higher the productivity is. This is a direct evidence of the impact of investment climate on productivity. And the coefficients on the interaction term of backward linkage variable and the ownership variable are significant and positive for most of the specifications. This shows the evidence of a positive incremental effect of investment climate on FDI spillovers via backward linkages. The higher the ownership limit a country has, the more the upstream company's productivity improves in response to more foreign presence. This finding is consistent with the finding from the FDI literature. Aghion et al. (2005) developed a model to understand that firms are more likely to adopt new technology hence increase productivity in a more open and competitive environment. Blalock and Gertler (2008) and Abraham et al. (2010) show evidence that more competitive environment leads to more productivity spillovers. Moran et al. (2005) also argue that restrictive FDI policies such as foreign equity restrictions will harm rather than boost economic development.

Table .13 uses another IAB measure, the index of easiness of setting up a foreign business. Because most coefficients on the index are positive, there is evidence that easiness of setting up foreign business have a direct productivity gain. However, unlike the previous results, easiness to set up foreign business hardly affects FDI spillovers. This index measures how the institutional environment encourage the entry of FDI. Unlike "hard" factors such as FDI law and regulations, this indicator reflects the soft side of government effectiveness regarding FDI inflows. Kaufmann et al. (1999) find that government effectiveness appeared to a significant determinant of FDI. Results from Table 13 complement their finding by showing the evidence of a correlation between government effectiveness and FDI productivity gain.

Table .14 shows the results using the number of procedures required to start foreign business. This indicator also reflects the effectiveness of a government. More complicated procedures suggest a less efficient government. First, there is a direct effect of number of procedures on productivity. Most of the coefficient on number of procedures are negative, meaning that the less procedures to set up a foreign business, the more productivity a country gains. The coefficients on the interaction term with backward linkages show mixed results. This indicates that number of procedures have an ambiguous effect on spillovers via backward linkages.

In addition to number of procedures to set up foreign business, Table .15 analyzes the time to set up foreign business. It is a nice complement to the first two indicators that reflect the effectiveness of institution to serve foreign direct investment. The negative and significant coefficients indicate that such a measure of investment climate might have an enhancing effect of productivity. The coefficients for the interaction term with forward linkages are negative, which implies less time in setting up foreign business might increase productivity via forward linkage. However, positive coefficient indicate an adverse incremental spillover effect of time on productivity via backward linkage. Similar to the establishment of business indices, the next two indicators above also to some extent reflect the effectiveness of a government. The time spent to lease public or private land could involve a number of procedures. And the more procedures the institution requires, the longer the process will be. Existing literature only draws conclusion on more aggregate measures of government measures and did not break down to various aspects of government effectiveness. These new indicators are excellent contribution to the current FDI literature. Table .16 shows the effect of time to lease public land. The direct effect of this measure on productivity is mixed. The coefficients on the interactions with the forward spillovers linkage appear significant and positive, which suggest a weakening effect for the forward spillovers. The measurement with time to lease private land is explored in Table .17. First, the coefficients on this measurement are positive. This indicates the counter-intuitive effect that longer time might be value-adding. And positive and negative coefficients on the interaction terms with forward and backward suggests weakening effect for FDI spillovers via forward linkages and enhancing effect via backward linkages.

Table .18 shows the results with measurement of availability of land information. Negative signs on the land information availability measure and interaction with the horizontal variable imply a negative direct productivity effect and a negative FDI spillovers effect through horizontal linkages. Access to land index is analyzed in Table .19. Similar to the previous measure, all the negative coefficients seem to suggest results that better access to information lead to less productivity and lower spillover effects. Information asymmetry has been known to be a crucial barrier to foreign investment. There has been a series of important research that studies the relationship between information and FDI. But such research remains small because of the lack of data. The results from this paper contributes to our understanding of this issue. Rodrik and Hausmann (2004) and Wells and Wint (2000) argue that providing credible and up-to-date information is yield significant social returns. In this research, however, such a productivity gain does not have empirical support from my data.

The next set of investment climate indicators measures the strength of law and protection of property rights. Aizenman and Spiegel (2006) shows theoretically that FDI should be worse in weaker enforcement of property rights due to the difference in ex-post monitoring cost between foreign and domestic investors. La Porta et al. (1998) and Kaufmann et al. (1999) provide empirical support of this view. However, to the my knowledge there has not been any theoretical research that studies how the strength of law and property rights protection affects the gain from FDI has not been tested before. This is the first research to provide empirical evidence of this issue. Table .20 shows the effect of strength of lease rights on productivity. It seems to suggest a negative effect for the productivity gain for weaker lease rights. The spillover effects through various channels show mixed results. The extent of judicial assistant measures legal environment for foreign investment. Table .21 shows empirical results using this measure. Positive coefficients on this measure suggest positive direct productivity effects. But negative coefficient for the interaction term indicates a weakening effect for the FDI spillovers via the backward linkage. The IAB ease of process indicator for arbitrating commercial disputes reflects another aspect of a country's legal environment. Estimations in Table .22 suggest a negative direct productivity effect and a negative incremental effect on FDI spillovers via backward linkages. But there is evidence of a spillovers enhancing effect through forward linkages. Table .23 shows the IAB strength of law indicator's effect. Negative coefficients on this measure suggest negative productivity effect. There seems to be some evidence of positive productivity effect through backward linkage.

The results in this paper vary a lot for different measures of investment climate. The ownership limit measure seems to have both direct positive effect on productivity and positive incremental effect on productivity spillovers through backward linkage. Such a results is consistent with the findings of the existing literature. The three starting foreign business indicators show positive direct effect on productivity but mixed results on incremental spillover effect. It provides some evidence in support of the current view in academia regarding the relationship of government effectiveness and FDI. The other two categories of indicators show results that are more noisy. Nonetheless they provide new evidence for the set of important issues that have not been studied much in the literature before due to the scarcity of cross-country and reliable data.

## 3.6 Conclusion

This paper studies productivity spillovers to domestic firms from foreign direct investment (FDI). Such productivity gain from FDI is considered to be the basis of policies that promote FDI all around the world. Although such policies are widely adopted, they are still under debate both in the policy and academic arena. The contribution of this paper is to provide new evidence and justification on how investment climate could impact productivity gain.

The new World Bank's *Investing Across Borders* dataset which records and scores a country's FDI environment in foreign ownership restrictions, establishment of foreign business, land access and strength of law, plus a large panel data of European firms provides great opportunity to study the important issue on how a country's investment environment impact productivity gain, either by evidence of a direct effect, or via externalities on upstream industry. This research contributes to the existing literature by a set of novel empirical results regarding different aspects of investment climate.

Consistent with the existing literature, this paper suggests that ownership has a significant positive impact on productivity gain of FDI. It suggests that allowing more foreign ownership could have a favorable impact on economic development. There is also some evidence that more effective procedure to establish business also have a positive effect. Removing restriction or improving procedure could have a positive effect on productivity. However, the results vary significant for different measures of investment climate. The effect of changes in land restrictions and legal environment could yield more mixed results on FDI.

This research studies the relationship between the institutional structure and FDI. However, there has been many other aspects of FDI policies that has not been addressed. For instance, the tax breaks, subsidies and special economic incentives are normally used by developing countries normally to attract FDI inflows. Infrasound and human capital development are also issues matter significantly for FDI. Moran et al. (2005) suggest that developing countries could devote more resources to overcome the imperfection of information supply, infrastructure improvement, education and training initiatives that can benefit foreign and domestic firms alike.

Table .1: Summary Statistics of IAB Indicators

| | Mean | Standard Deviation | Average Ownership | Start Foreign Business: Ease of Process | Start Foreign Business: Procedures | Start Foreign Business: Time in Days | Time to Lease Public Land | Time to Lease Private Land | Availability of Land Information | Access to Land Information | Strength of Ownership Rights | Strength of Leaser Rights | Extent of Judicial Assistant | Ease of Arbitrating Process | Strength of Laws |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Average Ownership | 91.08 | 3.62406 | 1 | | | | | | | | | | | | |
| Start Foreign Business: Ease of Process | 76.28 | 6.75893 | 0.7388 | 1 | | | | | | | | | | | |
| Start Foreign Business: Procedures | 10.28 | 3.0347 | -0.3409 | -0.8277 | 1 | | | | | | | | | | |
| Start Foreign Business: Time in Days | 39.65 | 24.1683 | -0.2638 | -0.7929 | 0.9601 | 1 | | | | | | | | | |
| Time to Lease Public Land | 108.1 | 46.7678 | -0.0693 | 0.0698 | -0.4892 | -0.3406 | 1 | | | | | | | | |
| Time to Lease Private Land | 56.52 | 33.1936 | 0.055 | 0.5831 | -0.7897 | -0.6976 | 0.5281 | 1 | | | | | | | |
| Availability of Land Information | 87.8 | 6.2371 | -0.3956 | -0.5489 | 0.3695 | 0.1938 | -0.093 | -0.684 | 1 | | | | | | |
| Access to Land Information | 51.89 | 11.3986 | -0.6076 | -0.9435 | 0.9078 | 0.8231 | -0.263 | -0.658 | 0.5462 | 1 | | | | | |
| Strength of Ownership Rights | 100 | 0 | | | | | | | | | | | | | |
| Strength of Leaser Rights | 96.35 | 6.72057 | -0.8306 | -0.8378 | 0.5943 | 0.4413 | -0.217 | -0.562 | 0.79 | 0.7852 | | 1 | | | |
| Extent of Judicial Assistant | 81.77 | 8.99609 | 0.0596 | 0.6517 | -0.7785 | -0.8856 | -0.02 | 0.4882 | -0.0481 | -0.6865 | | -0.161 | 1 | | |
| Ease of Arbitrating Process | 78.47 | 4.98726 | -0.5155 | 0.1357 | -0.4534 | -0.536 | 0.1938 | 0.7119 | -0.1925 | -0.1664 | | 0.1058 | 0.569 | 1 | |
| Strength of Laws | 92.43 | 6.67248 | -0.4902 | -0.8701 | 0.8142 | 0.6966 | -0.245 | -0.843 | 0.8283 | 0.9014 | | 0.845 | -0.5388 | -0.3548 | 1 |

Table .2: Input-Output Tables

| Years: | 2005 | 2006 | 2007 | 2008 |
|---|---|---|---|---|
| Bulgaria | 2005 | 2005 | 2005 | 2005 |
| Czech Republic | 2005 | 2006 | 2007 | 2007 |
| France | 2005 | 2006 | 2007 | 2007 |
| Poland | 2005 | 2006 | 2006 | 2006 |
| Romania | 2004 | 2006 | 2007 | 2007 |
| Spain | 2005 | 2006 | 2007 | 2007 |

Table .3: Summary Statistics for Key Variables

| Countries | (1) Bulgaria | (2) Czech Republic | (3) France | (4) Poland | (5) Romania | (6) Spain | (7) Overall |
|---|---|---|---|---|---|---|---|
| logY | | | | | | | |
| Mean | 14.1 | 17.2 | 8.5 | 15.7 | 12.6 | 13.9 | 12.7 |
| Std. Dev. | 1.92 | 2.21 | 1.64 | 1.83 | 1.88 | 1.76 | 2.90 |
| No. Obs. | 14,863 | 5,547 | 142,568 | 42,516 | 97,858 | 368,609 | 671,961 |
| logL | | | | | | | |
| Mean | 3.2 | 3.8 | 3.2 | 3.3 | 1.5 | 2.2 | 2.4 |
| Std. Dev. | 1.71 | 1.83 | 1.46 | 1.41 | 1.33 | 1.40 | 1.54 |
| No. Obs. | 14,863 | 5,547 | 142,568 | 42,516 | 97,858 | 368,609 | 671,961 |
| logK | | | | | | | |
| Mean | 12.9 | 15.2 | 6.1 | 13.6 | 11.2 | 12.1 | 10.8 |
| Std. Dev | 2.51 | 2.75 | 2.16 | 2.48 | 2.37 | 2.29 | 3.43 |
| No. Obs. | 14,325 | 5,247 | 141,277 | 40,545 | 87,151 | 361,322 | 649,867 |
| logM | | | | | | | |
| Mean | 11.6 | 16.0 | 7.1 | 14.6 | 11.1 | 13.0 | 11.6 |
| Std. Dev | 2.57 | 2.69 | 2.35 | 2.43 | 2.57 | 2.22 | 3.41 |
| No. Obs. | 14,863 | 5,545 | 141,199 | 42,510 | 97,810 | 363,113 | 665,040 |
| Foreign Share | | | | | | | |
| Mean | 0.2 | 0.6 | 0.1 | 0.2 | 0.2 | 0.03 | 0.09 |
| Std. Dev | 0.39 | 0.48 | 0.26 | 0.36 | 0.41 | 0.17 | 0.27 |
| No. Obs. | 14,863 | 5,547 | 142,568 | 42,516 | 97,858 | 368,609 | 671,961 |
| Horizontal | | | | | | | |
| Mean | 0.254 | 0.618 | 0.128 | 0.331 | 0.445 | 0.149 | 0.206 |
| Std. Dev | 0.18 | 0.21 | 0.10 | 0.16 | 0.17 | 0.10 | 0.17 |
| No. Obs. | 14,863 | 5,547 | 142,568 | 42,516 | 97,858 | 368,609 | 671,961 |
| Forward | | | | | | | |
| Mean | 0.268 | 0.586 | 0.150 | 0.372 | 0.551 | 0.176 | 0.246 |
| Std. Dev | 0.13 | 0.13 | 0.04 | 0.11 | 0.11 | 0.05 | 0.16 |
| No. Obs. | 11,579 | 3,638 | 112,562 | 32,651 | 83,774 | 287,277 | 531,481 |
| Backward | | | | | | | |
| Mean | 0.209 | 0.558 | 0.127 | 0.344 | 0.292 | 0.152 | 0.185 |
| Std. Dev | 0.16 | 0.14 | 0.04 | 0.12 | 0.23 | 0.04 | 0.13 |
| No. Obs. | 11,579 | 3,638 | 112,562 | 32,651 | 83,774 | 287,277 | 531,481 |

Table .4: Summary Statistics for Spillover Variables (Bulgaria)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Years | 2005 | 2006 | 2007 | 2008 |
| Horizontal | | | | |
| Mean | 0.147 | 0.283 | 0.257 | 0.391 |
| Std. Dev | 0.113 | 0.176 | 0.176 | 0.214 |
| No. Obs. | 2913 | 5237 | 5629 | 1084 |
| Forward | | | | |
| Mean | 0.106 | 0.276 | 0.350 | 0.547 |
| Std. Dev | 0.046 | 0.074 | 0.087 | 0.085 |
| No. Obs. | 2897 | 5114 | 2905 | 663 |
| Backward | | | | |
| Mean | 0.081 | 0.183 | 0.324 | 0.460 |
| Std. Dev | 0.066 | 0.125 | 0.145 | 0.166 |
| No. Obs. | 2897 | 5114 | 2905 | 663 |

Table .5: Summary Statistics for Spillover Variables (Czech Republic)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Years | 2005 | 2006 | 2007 | 2008 |
| Horizontal | | | | |
| Mean | 0.726 | 0.625 | 0.615 | 0.555 |
| Std. Dev | 0.193 | 0.186 | 0.192 | 0.234 |
| No. Obs. | 688 | 1523 | 2129 | 1207 |
| Forward | | | | |
| Mean | 0.690 | 0.612 | 0.547 | 0.492 |
| Std. Dev | 0.108 | 0.068 | 0.113 | 0.163 |
| No. Obs. | 652 | 1278 | 1075 | 633 |
| Backward | | | | |
| Mean | 0.676 | 0.580 | 0.517 | 0.460 |
| Std. Dev | 0.116 | 0.059 | 0.131 | 0.168 |
| No. Obs. | 652 | 1278 | 1075 | 633 |

Table .6: Summary Statistics for Spillover Variables (France)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Years | 2005 | 2006 | 2007 | 2008 |
| Horizontal | | | | |
| Mean | 0.127 | 0.137 | 0.133 | 0.112 |
| Std. Dev | 0.092 | 0.101 | 0.101 | 0.093 |
| No. Obs. | 35357 | 40417 | 31647 | 35147 |
| Forward | | | | |
| Mean | 0.170 | 0.146 | 0.148 | 0.120 |
| Std. Dev | 0.029 | 0.034 | 0.037 | 0.027 |
| No. Obs. | 35200 | 38992 | 21894 | 16476 |
| Backward | | | | |
| Mean | 0.120 | 0.146 | 0.116 | 0.112 |
| Std. Dev | 0.039 | 0.047 | 0.026 | 0.043 |
| No. Obs. | 35200 | 38992 | 21894 | 16476 |

Table .7: Summary Statistics for Spillover Variables (Poland)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Years | 2005 | 2006 | 2007 | 2008 |
| Horizontal | | | | |
| Mean | 0.320 | 0.331 | 0.335 | 0.337 |
| Std. Dev | 0.177 | 0.150 | 0.169 | 0.169 |
| No. Obs. | 5965 | 18870 | 10417 | 7264 |
| Forward | | | | |
| Mean | 0.357 | 0.373 | 0.411 | 0.333 |
| Std. Dev | 0.082 | 0.078 | 0.153 | 0.152 |
| No. Obs. | 5910 | 18123 | 5090 | 3528 |
| Backward | | | | |
| Mean | 0.365 | 0.349 | 0.360 | 0.262 |
| Std. Dev | 0.088 | 0.107 | 0.169 | 0.145 |
| No. Obs. | 5910 | 18123 | 5090 | 3528 |

Table .8: Summary Statistics for Spillover Variables (Romania)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Years | 2005 | 2006 | 2007 | 2008 |
| Horizontal | | | | |
| Mean | 0.493 | 0.500 | 0.476 | 0.267 |
| Std. Dev | 0.131 | 0.123 | 0.258 | 0.152 |
| No. Obs. | 38338 | 36855 | 1044 | 21621 |
| Forward | | | | |
| Mean | 0.566 | 0.571 | 0.570 | 0.389 |
| Std. Dev | 0.093 | 0.097 | 0.172 | 0.098 |
| No. Obs. | 38338 | 36855 | 382 | 8199 |
| Backward | | | | |
| Mean | 0.289 | 0.283 | 0.452 | 0.342 |
| Std. Dev | 0.239 | 0.242 | 0.194 | 0.132 |
| No. Obs. | 38338 | 36855 | 382 | 8199 |

Table .9: Summary Statistics for Spillover Variables (Spain)

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Years | 2005 | 2006 | 2007 | 2008 |
| Horizontal | | | | |
| Mean | 0.168 | 0.150 | 0.135 | 0.489 |
| Std. Dev | 0.109 | 0.103 | 0.093 | 0.304 |
| No. Obs. | 102656 | 126336 | 139395 | 222 |
| Forward | | | | |
| Mean | 0.170 | 0.168 | 0.198 | 0.428 |
| Std. Dev | 0.043 | 0.042 | 0.045 | 0.194 |
| No. Obs. | 101408 | 117642 | 68111 | 116 |
| Backward | | | | |
| Mean | 0.153 | 0.144 | 0.165 | 0.432 |
| Std. Dev | 0.034 | 0.034 | 0.066 | 0.180 |
| No. Obs. | 101408 | 117642 | 68111 | 116 |

Table .10: OLS regressions

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| Countries | Bulgaria | Czech Republic | France | Poland | Romania | Spain | Overall |
| Dep Var: dlnY | | | | | | | |
| dlnL | 0.257*** | 0.0464 | 0.244*** | 0.0644*** | 0.248*** | 0.198*** | 0.206*** |
| | (0.0236) | (0.0409) | (0.00445) | (0.0113) | (0.00741) | (0.00288) | (0.00236) |
| dlnK | 0.0275** | 0.412*** | 0.0424*** | 0.0965*** | 0.0592*** | 0.0691*** | 0.0707*** |
| | (0.0139) | (0.0186) | (0.00262) | (0.00617) | (0.00370) | (0.00175) | (0.00135) |
| dlnM | 0.250*** | 0.499*** | 0.274*** | 0.572*** | 0.427*** | 0.449*** | 0.428*** |
| | (0.0127) | (0.0184) | (0.00228) | (0.00621) | (0.00376) | (0.00143) | (0.00118) |
| dforeignshare | 0.0636 | -0.0978 | 0.00704 | -0.133*** | -0.00137 | 0.0271 | 0.00576 |
| | (0.0959) | (0.0804) | (0.0137) | (0.0396) | (0.0366) | (0.0222) | (0.0127) |
| dhorizontal | -0.0409 | -0.0531 | -0.0344** | 0.0745** | -0.0492 | -0.0347 | -0.0251** |
| | (0.0595) | (0.0734) | (0.0149) | (0.0348) | (0.0554) | (0.0217) | (0.0126) |
| dforward | -0.0330 | 0.190 | -0.0380 | -0.0625* | -0.389*** | -0.222*** | -0.0985*** |
| | (0.125) | (0.143) | (0.0364) | (0.0363) | (0.104) | (0.0327) | (0.0199) |
| dbackward | 0.0557 | -0.175 | -0.0734** | 0.0248 | 0.281** | 0.175*** | 0.0829*** |
| | (0.0918) | (0.127) | (0.0287) | (0.0307) | (0.112) | (0.0257) | (0.0168) |
| No. Obs. | 3,973 | 588 | 41,827 | 6,908 | 26,376 | 122,030 | 201,702 |
| R squared | 0.158 | 0.905 | 0.349 | 0.617 | 0.418 | 0.505 | 0.461 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY as the dependent variable. logL, logM and logK are included as regressors along with the firm-level controls, sector-level FDI variables.
*Significant at 10-percent level
**Significant at 5-percent level

***Significant at 1-percent level

Table .11: OLS regressions (Two Stages)

| Countries | (1)<br>Bulgaria | (2)<br>Czech Republic | (3)<br>France | (4)<br>Poland | (5)<br>Romania | (6)<br>Spain | (7)<br>Overall |
|---|---|---|---|---|---|---|---|
| *First Stage:* | | | | | | | |
| Dep Var: dlnY | | | | | | | |
| dlnL | 0.274*** | 0.0912* | 0.243*** | 0.0885*** | 0.294*** | 0.205*** | 0.216*** |
| | (0.0192) | (0.0491) | (0.00399) | (0.00864) | (0.00767) | (0.00233) | (0.00201) |
| dlnK | 0.0601*** | 0.437*** | 0.0482*** | 0.0883*** | 0.0849*** | 0.0687*** | 0.0768*** |
| | (0.0115) | (0.0186) | (0.00232) | (0.00490) | (0.00377) | (0.00138) | (0.00114) |
| dlnM | 0.280*** | 0.456*** | 0.296*** | 0.586*** | 0.349*** | 0.442*** | 0.413*** |
| | (0.0107) | (0.0188) | (0.00205) | (0.00522) | (0.00351) | (0.00118) | (0.00101) |
| *Second Stage:* | | | | | | | |
| Dep Var: dlnTFP | | | | | | | |
| dforeignshare | 0.0645 | -0.0938 | 0.00655 | -0.132*** | 0.00239 | 0.0269 | 0.00565 |
| | (0.0960) | (0.0805) | (0.0137) | (0.0396) | (0.0369) | (0.0222) | (0.0128) |
| dhorizontal | -0.0416 | -0.0490 | -0.0358** | 0.0762** | -0.0505 | -0.0348 | -0.0250** |
| | (0.0596) | (0.0735) | (0.0149) | (0.0348) | (0.0559) | (0.0217) | (0.0126) |
| dforward | -0.0305 | 0.173 | -0.0388 | -0.0607* | -0.424*** | -0.224*** | -0.103*** |
| | (0.125) | (0.144) | (0.0364) | (0.0363) | (0.105) | (0.0327) | (0.0199) |
| dbackward | 0.0623 | -0.183 | -0.0743*** | 0.0252 | 0.236** | 0.178*** | 0.0850*** |
| | (0.0919) | (0.127) | (0.0287) | (0.0307) | (0.112) | (0.0257) | (0.0168) |
| No. Obs. | 3,973 | 588 | 41,827 | 6,908 | 26,376 | 122,030 | 201,702 |
| R squared | 0.005 | 0.022 | 0.001 | 0.004 | 0.004 | 0.001 | 0.001 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY as the dependent variable. logL, logM and logK are included as regressors along with the firm-level controls, sector-level FDI variables.
*Significant at 10-percent level
**Significant at 5-percent level

***Significant at 1-percent level

Table .12: Regressions, Average Ownership

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.112*** |
| | (0.00237) | (0.00201) | (0.00180) |
| dlnK | 0.0672*** | 0.0751*** | 0.116*** |
| | (0.00135) | (0.00114) | (0.00668) |
| dlnM | 0.428*** | 0.412*** | 0.566*** |
| | (0.00118) | (0.00101) | (0.00130) |
| dforeignshare | 0.000129 | 0.000376 | -0.00522 |
| | (0.0127) | (0.0127) | (0.0132) |
| dhorizontal | 0.170 | 0.165 | 0.311 |
| | (0.265) | (0.265) | (0.275) |
| dforward | -0.152 | -0.171 | -0.635 |
| | (0.476) | (0.476) | (0.494) |
| dbackward | -1.780*** | -1.750*** | -1.974*** |
| | (0.423) | (0.423) | (0.439) |
| IAB indicator | 0.00320*** | 0.00307*** | 0.00264*** |
| | (0.000296) | (0.000295) | (0.000307) |
| dhorizontal*IAB indicator | -0.00224 | -0.00219 | -0.00383 |
| | (0.00288) | (0.00288) | (0.00299) |
| dforward*IAB indicator | -0.000130 | 4.58e-05 | 0.00526 |
| | (0.00514) | (0.00514) | (0.00534) |
| dbackward*IAB indicator | 0.0203*** | 0.0200*** | 0.0223*** |
| | (0.00462) | (0.00462) | (0.00480) |
| No. Obs. | 201,696 | 201,696 | 201,704 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).

*Significant at 10-percent level

**Significant at 5-percent level

***Significant at 1-percent level

Table .13: Regressions, Ease of Establishment Index

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.113*** |
| | (0.00237) | (0.00201) | (0.00135) |
| dlnK | 0.0686*** | 0.0761*** | 0.124*** |
| | (0.00136) | (0.00114) | (0.0474) |
| dlnM | 0.428*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00131) |
| dforeignshare | -0.00151 | -0.00150 | -0.00356 |
| | (0.0128) | (0.0128) | (0.0133) |
| dhorizontal | -0.0452 | -0.0524 | 0.208 |
| | (0.168) | (0.168) | (0.175) |
| dforward | -0.463* | -0.486* | -0.430 |
| | (0.257) | (0.257) | (0.268) |
| dbackward | 0.150 | 0.195 | -0.229 |
| | (0.220) | (0.220) | (0.229) |
| IAB indicator | 0.00159*** | 0.00154*** | 0.00137*** |
| | (0.000152) | (0.000152) | (0.000158) |
| dhorizontal*IAB indicator | 6.09e-05 | 0.000161 | -0.00328 |
| | (0.00216) | (0.00216) | (0.00224) |
| dforward*IAB indicator | 0.00452 | 0.00477 | 0.00419 |
| | (0.00329) | (0.00329) | (0.00342) |
| dbackward*IAB indicator | -0.000841 | -0.00140 | 0.00388 |
| | (0.00284) | (0.00285) | (0.00296) |
| No. Obs. | 201,699 | 201,699 | 201,698 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).

*Significant at 10-percent level

**Significant at 5-percent level

***Significant at 1-percent level

Table .14: Regressions, Procedures to Start Foreign Business

| Method | (1) OLS | (2) Two Stage OLS | (3) Two Stage Olley-Pakes |
|---|---|---|---|
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.113*** |
| | (0.00237) | (0.00201) | (0.00222) |
| dlnK | 0.0691*** | 0.0761*** | 0.124*** |
| | (0.00135) | (0.00114) | (0.0453) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00124) |
| dforeignshare | 0.00308 | 0.00286 | 1.83e-05 |
| | (0.0127) | (0.0127) | (0.0133) |
| dhorizontal | -0.0786** | -0.0774** | -0.0919** |
| | (0.0380) | (0.0380) | (0.0395) |
| dforward | 0.171*** | 0.171*** | 0.150** |
| | (0.0585) | (0.0585) | (0.0609) |
| dbackward | -0.0794 | -0.0856 | 0.00499 |
| | (0.0540) | (0.0540) | (0.0562) |
| IAB indicator | -0.00271*** | -0.00268*** | -0.00261*** |
| | (0.000331) | (0.000331) | (0.000345) |
| dhorizontal*IAB indicator | 0.00393 | 0.00382 | 0.00450 |
| | (0.00406) | (0.00406) | (0.00423) |
| dforward*IAB indicator | -0.0305*** | -0.0309*** | -0.0275*** |
| | (0.00620) | (0.00620) | (0.00645) |
| dbackward*IAB indicator | 0.0171*** | 0.0179*** | 0.00649 |
| | (0.00542) | (0.00542) | (0.00564) |
| No. Obs. | 201,699 | 201,699 | 201,698 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).

*Significant at 10-percent level

**Significant at 5-percent level

***Significant at 1-percent level

Table .15: Regressions, Time to Start Foreign Business

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.113*** |
| | (0.00237) | (0.00201) | (0.00169) |
| dlnK | 0.0691*** | 0.0761*** | 0.124*** |
| | (0.00135) | (0.00114) | (0.0345) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00275) |
| dforeignshare | 0.00273 | 0.00250 | -0.000289 |
| | (0.0127) | (0.0127) | (0.0133) |
| dhorizontal | -0.0615*** | -0.0601*** | -0.0835*** |
| | (0.0217) | (0.0217) | (0.0225) |
| dforward | 0.0997*** | 0.0953** | 0.0882** |
| | (0.0382) | (0.0382) | (0.0398) |
| dbackward | -0.0286 | -0.0314 | 0.0180 |
| | (0.0344) | (0.0344) | (0.0358) |
| IAB indicator | -0.000326*** | -0.000322*** | -0.000315*** |
| | (4.10e-05) | (4.10e-05) | (4.26e-05) |
| dhorizontal*IAB indicator | 0.000656 | 0.000618 | 0.00111* |
| | (0.000571) | (0.000571) | (0.000594) |
| dforward*IAB indicator | -0.00553*** | -0.00554*** | -0.00495*** |
| | (0.000942) | (0.000943) | (0.000981) |
| dbackward*IAB indicator | 0.00313*** | 0.00326*** | 0.00145* |
| | (0.000799) | (0.000800) | (0.000832) |
| No. Obs. | 201,699 | 201,699 | 201,698 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).

*Significant at 10-percent level

**Significant at 5-percent level

***Significant at 1-percent level

Table .16: Regressions, Time to Lease Public Land in Days

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.113*** |
| | (0.00237) | (0.00201) | (0.00118) |
| dlnK | 0.0694*** | 0.0761*** | 0.124** |
| | (0.00135) | (0.00114) | (0.0541) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00211) |
| dforeignshare | 0.00866 | 0.00844 | 0.00584 |
| | (0.0127) | (0.0127) | (0.0133) |
| dhorizontal | 0.000521 | 0.00166 | -0.0290 |
| | (0.0243) | (0.0243) | (0.0253) |
| dforward | -0.233*** | -0.238*** | -0.207*** |
| | (0.0422) | (0.0422) | (0.0439) |
| dbackward | 0.0885** | 0.0941*** | 0.0636* |
| | (0.0359) | (0.0359) | (0.0373) |
| IAB indicator | 1.90e-05 | 2.45e-05 | 5.93e-05** |
| | (2.77e-05) | (2.77e-05) | (2.88e-05) |
| dhorizontal*IAB indicator | -0.000203 | -0.000213 | -8.01e-05 |
| | (0.000140) | (0.000140) | (0.000145) |
| dforward*IAB indicator | 0.000851*** | 0.000851*** | 0.000677*** |
| | (0.000246) | (0.000246) | (0.000256) |
| dbackward*IAB indicator | -8.18e-05 | -0.000110 | -3.05e-05 |
| | (0.000230) | (0.000231) | (0.000240) |
| No. Obs. | 201,699 | 201,699 | 201,698 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).

*Significant at 10-percent level

**Significant at 5-percent level

***Significant at 1-percent level

Table .17: Regressions, Time to Lease Private Land in Days

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.113*** |
| | (0.00237) | (0.00201) | (0.00196) |
| dlnK | 0.0694*** | 0.0761*** | 0.121*** |
| | (0.00135) | (0.00114) | (0.0466) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00161) |
| dforeignshare | 0.00738 | 0.00711 | 0.00477 |
| | (0.0127) | (0.0127) | (0.0132) |
| dhorizontal | -0.0504* | -0.0520* | -0.0587** |
| | (0.0282) | (0.0282) | (0.0293) |
| dforward | -0.232*** | -0.240*** | -0.190*** |
| | (0.0400) | (0.0400) | (0.0416) |
| dbackward | 0.211*** | 0.216*** | 0.158*** |
| | (0.0331) | (0.0331) | (0.0344) |
| IAB indicator | 8.10e-05** | 8.14e-05** | 0.000116*** |
| | (3.29e-05) | (3.29e-05) | (3.42e-05) |
| dhorizontal*IAB indicator | 0.000368 | 0.000394 | 0.000278 |
| | (0.000376) | (0.000376) | (0.000391) |
| dforward*IAB indicator | 0.00185*** | 0.00191*** | 0.00140*** |
| | (0.000475) | (0.000475) | (0.000494) |
| dbackward*IAB indicator | -0.00176*** | -0.00181*** | -0.00127*** |
| | (0.000400) | (0.000400) | (0.000415) |
| No. Obs. | 201,699 | 201,699 | 201,702 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).
*Significant at 10-percent level
**Significant at 5-percent level

***Significant at 1-percent level

Table .18: Regressions, Availability of Land Information Index

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.113*** |
| | (0.00237) | (0.00201) | (0.00171) |
| dlnK | 0.0692*** | 0.0761*** | 0.121*** |
| | (0.00135) | (0.00114) | (0.0346) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00165) |
| dforeignshare | 0.00716 | 0.00696 | 0.00474 |
| | (0.0127) | (0.0127) | (0.0132) |
| dhorizontal | 0.253* | 0.260* | 0.158 |
| | (0.152) | (0.152) | (0.157) |
| dforward | -0.142 | -0.126 | -0.199 |
| | (0.169) | (0.169) | (0.176) |
| dbackward | -0.116 | -0.128 | -0.0491 |
| | (0.145) | (0.145) | (0.151) |
| IAB indicator | -0.000502** | -0.000465** | -0.000499** |
| | (0.000203) | (0.000203) | (0.000210) |
| dhorizontal*IAB indicator | -0.00316* | -0.00322* | -0.00222 |
| | (0.00171) | (0.00171) | (0.00178) |
| dforward*IAB indicator | 0.000526 | 0.000291 | 0.00127 |
| | (0.00196) | (0.00196) | (0.00204) |
| dbackward*IAB indicator | 0.00233 | 0.00250 | 0.00136 |
| | (0.00169) | (0.00169) | (0.00175) |
| No. Obs. | 201,699 | 201,699 | 201,702 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).

*Significant at 10-percent level

**Significant at 5-percent level

***Significant at 1-percent level

Table .19: Regressions, Access to Land Information

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.113*** |
| | (0.00237) | (0.00201) | (0.00171) |
| dlnK | 0.0687*** | 0.0761*** | 0.121*** |
| | (0.00135) | (0.00114) | (0.0344) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00132) |
| dforeignshare | -0.000583 | -0.000658 | -0.00185 |
| | (0.0128) | (0.0128) | (0.0133) |
| dhorizontal | -0.0629 | -0.0628 | -0.0819 |
| | (0.0539) | (0.0539) | (0.0560) |
| dforward | 0.0466 | 0.0488 | 0.0593 |
| | (0.0811) | (0.0811) | (0.0843) |
| dbackward | 0.0413 | 0.0307 | 0.150** |
| | (0.0731) | (0.0731) | (0.0760) |
| IAB indicator | -0.000949*** | -0.000926*** | -0.000807*** |
| | (9.14e-05) | (9.14e-05) | (9.49e-05) |
| dhorizontal*IAB indicator | 0.000369 | 0.000378 | 0.000556 |
| | (0.00108) | (0.00108) | (0.00112) |
| dforward*IAB indicator | -0.00342** | -0.00356** | -0.00350** |
| | (0.00166) | (0.00166) | (0.00172) |
| dbackward*IAB indicator | 0.000797 | 0.00105 | -0.00170 |
| | (0.00143) | (0.00143) | (0.00149) |
| No. Obs. | 201,699 | 201,699 | 201,702 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).
*Significant at 10-percent level
**Significant at 5-percent level

***Significant at 1-percent level

Table .20: Regressions, Strength of Lease Right Index

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.112*** |
| | (0.00237) | (0.00201) | (0.00173) |
| dlnK | 0.0687*** | 0.0761*** | 0.121*** |
| | (0.00136) | (0.00114) | (0.0135) |
| dlnM | 0.428*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00184) |
| dforeignshare | 0.000433 | 0.000410 | -0.00526 |
| | (0.0128) | (0.0128) | (0.0132) |
| dhorizontal | 0.0117 | 0.0161 | -0.0851 |
| | (0.156) | (0.156) | (0.162) |
| dforward | 0.0309 | 0.0536 | 0.0638 |
| | (0.216) | (0.216) | (0.224) |
| dbackward | 0.376** | 0.353* | 0.486** |
| | (0.182) | (0.182) | (0.189) |
| IAB indicator | -0.00167*** | -0.00161*** | -0.00148*** |
| | (0.000169) | (0.000169) | (0.000175) |
| dhorizontal*IAB indicator | -0.000539 | -0.000580 | 0.000411 |
| | (0.00166) | (0.00166) | (0.00172) |
| dforward*IAB indicator | -0.00186 | -0.00214 | -0.00205 |
| | (0.00233) | (0.00233) | (0.00242) |
| dbackward*IAB indicator | -0.00310 | -0.00283 | -0.00447** |
| | (0.00193) | (0.00193) | (0.00201) |
| No. Obs. | 201,699 | 201,699 | 201,704 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).
*Significant at 10-percent level
**Significant at 5-percent level

***Significant at 1-percent level

Table .21: Regressions, Extent of Judicial Assistance Index

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.112*** |
| | (0.00237) | (0.00201) | (0.00156) |
| dlnK | 0.0691*** | 0.0761*** | 0.121*** |
| | (0.00135) | (0.00114) | (0.0364) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00218) |
| dforeignshare | 0.00451 | 0.00429 | -0.00160 |
| | (0.0127) | (0.0127) | (0.0132) |
| dhorizontal | 0.137 | 0.130 | 0.221** |
| | (0.100) | (0.100) | (0.104) |
| dforward | -0.305* | -0.297 | -0.226 |
| | (0.183) | (0.183) | (0.190) |
| dbackward | 1.009*** | 1.029*** | 0.668*** |
| | (0.163) | (0.163) | (0.169) |
| IAB indicator | 0.000633*** | 0.000622*** | 0.000566*** |
| | (0.000112) | (0.000112) | (0.000116) |
| dhorizontal*IAB indicator | -0.00205* | -0.00197 | -0.00320** |
| | (0.00122) | (0.00122) | (0.00127) |
| dforward*IAB indicator | 0.00253 | 0.00235 | 0.00177 |
| | (0.00231) | (0.00231) | (0.00240) |
| dbackward*IAB indicator | -0.0117*** | -0.0119*** | -0.00761*** |
| | (0.00204) | (0.00204) | (0.00212) |
| No. Obs. | 201,699 | 201,699 | 201,704 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).
*Significant at 10-percent level
**Significant at 5-percent level

***Significant at 1-percent level

Table .22: Regressions, Ease of Process Index

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.112*** |
| | (0.00237) | (0.00201) | (0.00156) |
| dlnK | 0.0691*** | 0.0761*** | 0.121*** |
| | (0.00135) | (0.00114) | (0.0364) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00221) |
| dforeignshare | 0.00678 | 0.00651 | 0.000659 |
| | (0.0127) | (0.0127) | (0.0132) |
| dhorizontal | -0.0615 | -0.0688 | 0.0281 |
| | (0.133) | (0.133) | (0.138) |
| dforward | -0.686*** | -0.697*** | -0.367 |
| | (0.226) | (0.226) | (0.235) |
| dbackward | 1.548*** | 1.562*** | 1.436*** |
| | (0.216) | (0.216) | (0.224) |
| IAB indicator | -0.000675*** | -0.000637*** | -0.000228 |
| | (0.000215) | (0.000215) | (0.000223) |
| dhorizontal*IAB indicator | 0.000518 | 0.000612 | -0.000768 |
| | (0.00169) | (0.00169) | (0.00176) |
| dforward*IAB indicator | 0.00707** | 0.00717** | 0.00326 |
| | (0.00290) | (0.00290) | (0.00301) |
| dbackward*IAB indicator | -0.0186*** | -0.0188*** | -0.0175*** |
| | (0.00273) | (0.00273) | (0.00284) |
| No. Obs. | 201,699 | 201,699 | 201,704 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).
*Significant at 10-percent level
**Significant at 5-percent level

***Significant at 1-percent level

Table .23: Regressions, Strength of Laws Index

| | (1) | (2) | (3) |
|---|---|---|---|
| Method | OLS | Two Stage OLS | Two Stage Olley-Pakes |
| Dep Var: dlnY | | | |
| dlnL | 0.207*** | 0.216*** | 0.112*** |
| | (0.00237) | (0.00201) | (0.00156) |
| dlnK | 0.0690*** | 0.0761*** | 0.121*** |
| | (0.00135) | (0.00114) | (0.0364) |
| dlnM | 0.427*** | 0.412*** | 0.566*** |
| | (0.00119) | (0.00101) | (0.00157) |
| dforeignshare | 0.00305 | 0.00291 | -0.00319 |
| | (0.0127) | (0.0128) | (0.0132) |
| dhorizontal | 0.116 | 0.124 | -0.0503 |
| | (0.176) | (0.176) | (0.183) |
| dforward | 0.144 | 0.163 | 0.0264 |
| | (0.212) | (0.212) | (0.220) |
| dbackward | -0.234 | -0.261 | -0.000271 |
| | (0.180) | (0.180) | (0.187) |
| IAB indicator | -0.00121*** | -0.00117*** | -0.00114*** |
| | (0.000166) | (0.000166) | (0.000172) |
| dhorizontal*IAB indicator | -0.00165 | -0.00173 | 7.39e-05 |
| | (0.00192) | (0.00192) | (0.00200) |
| dforward*IAB indicator | -0.00275 | -0.00302 | -0.00130 |
| | (0.00235) | (0.00235) | (0.00244) |
| dbackward*IAB indicator | 0.00354* | 0.00385* | 0.000751 |
| | (0.00198) | (0.00198) | (0.00206) |
| No. Obs. | 201,699 | 201,699 | 201,704 |

Notes: Robust clustered standard errors are presented in parentheses. In estimates using logY (i.e., in column (1) as the dependent variable, logL, logM, and logK are included as regressors along with the firm-level controls, sector-level FDI variables. In column (2) and (3), the estimation procedure is two-stage. In the first stage, we use the OP regression method to obtain estimates for the input coefficients and then calculate lnTFP (the residual from the production function). In the second stage, we regress lnTFP on the remaining controls (firm-level foreign share, state share, sector-level FDI variables, and interaction variables).
*Significant at 10-percent level
**Significant at 5-percent level

***Significant at 1-percent level

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