THREE ESSAYS IN CORPORATE FINANCE

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Declaration

I hereby declare that this thesis is my original work. I would like to thank the faculty in The Department of Accounting and Finance at the Lancaster University, especially my supervisors and my collegues in the department for all of their help and support. I would especially like to acknowledge the valuable conversations and meetings with Grzegorz Pawlina and Ingmar Nolte, who have provided a generous amount of useful comments. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously. Chapter 2 and Chapter 4 are based on papers that are co-authored with Ingmar Nolte and Grzegorz Pawlina. Chapter 3 is based on a single-authored working paper.

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Abstract

This dissertation is comprised of three stand-alone essays in the field of corporate finance. Chapter 1 provides an introduction and overview of the three essays (Chapter 2-4). Chapter 2 explores the driving force behind the observed declining pattern of investment-cash flow sensitivity, which has puzzled empirical researchers for a decade. It investigates the variation of capital adjustment costs in explaining the investment-cash flow sensitivity and shows that the decreasing trend of the investment-cash flow sensitivity can be explained by the gradually increasing costs of capital adjustment. Chapter 3 studies the behavior of the firms in the aftermath of the 2007-09 financial crisis. A negative shock to the collateral value, which results in tightening the borrowing capacity, leads to a protracted recession of the firms' activities with the real business conditions unaffected. However, the effect of the collateral shock subsides when it coincides with a slowdown in the productivity. The reduction of labor adjustment costs causes investment and employment growth to decline more (less) aggressively with the negative productivity shock (collateral shock) and the trimming of labor adjustment costs fares better for the small firms. A flexible wage contract can significantly alleviate the negative impact of the collateral shock. While the equity issuance falls (rises) with the adverse productivity (collateral) shock, the cyclical behavior of equity financing is less pronounced for the more financially constrained firms. Chapter 4 is motivated by the endogeneity problem in standard regression methodologies, which may overlook the coefficient biases induced by the measurement error in the variables. The measurement error in Tobin's q, which operates via the covariance between q and cash flow, plays an

important part in explaining the time-series and cross-sectional pattern of investment-cash flow sensitivity. Moreover, even a high-order moment-based GMM estimator cannot address the bias if the measurement error is *not* independent of q (a non-classical error). Chapter 5 summarizes the main findings and concludes the thesis.

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Chapter 1

Introduction

Managers maximize firm value through choosing the optimal corporate investment, employment and financial decisions. Investment behavior is affected by a number of factors such as corporate productivity, adjustment technologies, fixed operating costs as well as internal financial resources and the availability of external sources of finance when the capital markets are imperfect. The interdependence between investment decision and financial factors is often examined using investment-q regressions augmented with cash flow. Chapter 2 attempts to explore the sensitivity of investment decisions to internal funds and to examine the conclusions based on the time-series pattern of the estimated investment-cash flow sensitivities. Furthermore, although the interactions between the firm's real activities and its financial constraints are largely explored, their relationship has received little attention in an environment where labor market frictions become an integral component. Chapter 3 investigates the long-term effect of a financial crisis on corporate decisions in the context of capital and labor dynamics. At the same time, the empirical inference of corporate investment decision can be invalid due to the measurement error in the variables and, thus, biased estimates of coefficients. Chapter 4 aims to investigate the measurement-error problem in Tobin's q and the way it leads to alternative explanations for the time-series and cross-sectional patterns of cash flow sensitivity. Chapter 5 summarizes the main findings and concludes the thesis.

Chapter 2 starts by referring to the observation that investment-cash flow sensitivity had been decreasing over time to disappear almost completely by late 2000s. The study shows that this pattern is consistent with the observed evolution of the capital adjustment costs in a neoclassical investment model with costly external financing. In particular, it estimates the magnitude of the capital adjustment cost parameter across different periods and shows that the decreasing pattern of the I-CF sensitivity can be explained by the gradually increasing costs of capital adjustment. The pattern of adjustment costs is supported by a broad set of tests ranging from a nonlinear estimation of the first order condition, a GMM estimation of Euler equation to a structural estimation of the parameters. Consistent with the prior literature, it finds no significant evidence of financial frictions contributing to the observed time-series pattern. The main results are further corroborated in a robustness analysis, which exploits the cross-industry and cross-country variation of capital adjustment costs.

Chapter 3 studies the implications of a financial crisis, which is associated with a large and prolonged deterioration to the collateral value and a depression to the economic outcomes such as investment, employment and output. I calibrate a model to explore the impact of the collateral shocks as well as the productivity shocks on the firm's real and financial variables. With the model-simulated data, I am able to disentangle the effect of credit supply shocks from the credit demand shocks by modeling productivity and collateral shocks as two independent random processes. I find that a negative shock to the collateral value, by tightening the borrowing capacity, leads to a deep decline and a subdued recovery of corporate activities with the real business conditions (productivity-driven) unaffected. Nonetheless, the impact of the collateral shock is mitigated by a slowdown in the productivity (a demand-side shock). I emphasize the empirical challenge faced by researchers: supply-effect subsides when the demand-effect presides during the financial crisis and any contraction of the firms' activity during the crisis period can hardly be ascribed to the shocks in the credit supply. Also, I examine how the impact of shocks varies with the nature of financial frictions and labor market frictions. The reduction of labor adjustment costs causes investment and employment growth to drop more significantly with the negative productivity shock but to decline less significantly with the negative collateral shock.

Chapter 4 is motivated by the fact that empirical finance research treats Tobin's q and cash flow as the explanatory variables despite the endogeneity problem arising from the measurement error in q. Nonetheless, the effect of measurement error, which operates via the covariance between q and cash flow, plays an important part in explaining the time-series and cross-sectional pattern of cash flow sensitivity. This chapter shows that measurement error diminishes investment-cash flow sensitivity in the recent periods because it biases cash flow sensitivity downward when q and cash flow are negatively covaried. The covariance structures also offer explanations for the perceived "wrong-way" differential cash flow sensitivity between constrained and unconstrained firms classified under the widely used *a priori* measures. Moreover, neither OLS estimators nor high-order moment-based GMM estimators can address the bias if the measurement error is not independent of q (a non-classical error).

Chapter 2

Can capital adjustment costs explain the decline in investment-cash flow sensitivity?

2.1 Introduction

One of key research areas in corporate finance is the effect of capital market imperfections on corporate investment. According to the standard q-investment model (Mussa 1977), the optimality condition equates the marginal value of capital (measured by the marginal q) with the marginal cost of investment. Marginal q is the sole factor relevant to the investment level. Financial factors, such as cash flow, are – in the absence of capital market frictions – irrelevant.

At the same time, a number of empirical studies that rely on a reduced-form regression model, which has investment as dependent variable and q and cash flow as independent variables, show that investment is sensitive to cash flow. Fazzari, Hubbard & Petersen (1988) interpret this investment-cash flow sensitivity as the evidence of financial constraints because financially constrained firms may link their investment to the availability of internal funds (see also Hoshi, Kashyap & Scharfstein 1991, Gilchrist & Himmelberg 1995, Lamont 1997). However, Fazzari et al.'s view that investment-cash flow sensitivity measures financial constraints has been challenged by, among others, Kaplan & Zingales (1997), Cleary (1999), Moyen (2004), Alti (2003), and Gomes

(2001). In particular, Erickson & Whited (2000, 2002) point out that the observed empirical investment-cash flow sensitivity can be spurious as Tobin's average q is a not a valid proxy for investment opportunities, due to the measurement error.[1]

The above contributions, however, base their conclusions on the cross-sectional comparison of the investment-cash flow (I-CF) sensitivity. Relatively few papers focus on its time-series pattern. Allayannis & Mozumdar (2004) are the first to observe a declining I-CF sensitivity from 1977-1986 to 1987-1996. Ağca & Mozumdar (2008) find that I-CF sensitivity decreases with factors that reduce capital market imperfections but without establishing a direct time-series link between I-CF sensitivity and these factors. More recently, Chen & Chen (2012) conclude that financial constraints cannot explain the declining pattern of I-CF sensitivity as there is no indication of financial constraints becoming more relaxed over time. They also document that the declining pattern of I-CF sensitivity still exists with measurement-error-corrected estimates. Although Brown & Petersen (2009) and Moshirian et al. (2017) conjecture that the declining I-CF sensitivity is due to the shift of importance from physical capital to intangible assets, Chen & Chen (2012) show that it is also R&D-cash flow sensitivity that disappears by late 2000s.[2] The declining trend of I-CF sensitivity therefore remains a puzzle.

In this chapter, we demonstrate that this time-series pattern is consistent with the evolution of the capital adjustment costs in a neoclassical investment model with costly external financing. We estimate the magnitude of the capital adjustment cost parameter across different periods and show that the decreasing pattern of the I-CF sensitivity can be explained by the gradually increasing costs of capital adjustment. Consistent with the prior literature, we find no evidence of financial frictions being able to significantly contribute to the observed time-series pattern. Most previous

[1] The (observable) Tobin's average q is equal to the marginal q if and only if the production function displays constant returns to scale in a competitive market and the adjustment cost function is linearly homogeneous to investment and capital (Hayashi 1982).

[2] Brown & Petersen (2009) report that cash flow sensitivity of total investment (physical capital expenditure and R&D expense) still decreases across periods.

studies examine how the financial situation of a firm affects its investment policy by adding cash flow to the regression and comparing the I-CF sensitivity across groups of firms sorted according to the characteristics that are assumed to capture the degree of financial constraints. In this chapter, rather than rely on a priori measures of financial constraints based on endogenous firm-level variables, we directly incorporate external financing costs into a dynamic investment model, which allows us to generate predictions about the effects of both financing frictions and capital adjustment costs. Subsequently, we estimate the magnitude of financing costs and adjustment costs over time as well as their effect on the time-series trend of the I-CF sensitivity.

Our results are consistent with those by Chen & Chen (2012) in the sense that declining I-CF sensitivity is not a symptom of decreasing financial constraints. (We measure the degree of financial constraints by estimating the parameter that captures the cost of accessing outside finance and find no evidence of the decreasing cost.) We demonstrate that the magnitude of I-CF sensitivity is not only an increasing function of financing constraints but also a decreasing function of capital adjustment costs. The intuition behind the latter result is as follows. When the firms invest out of internally-generated cash flow, it incurs capital adjustment costs, hence the presence of such costs lowers cash flow sensitivity of investment.[3] Given that investment depends less on the availability of internal funds when capital adjustment is more costly, a positive time trend in the adjustment costs would result in a declining I-CF sensitivity. Obtained empirical results support the hypothesis that it is a gradual increase of the adjustment cost parameter over time that significantly contributes to the observed declining I-CF sensitivity pattern.

The increasing capital adjustment costs argument is also consistent with the declining investment-q sensitivity as the frictions of adjusting capital temper the response of investment to the changes in growth opportunities captured by Tobin's q. It is further supported by the evidence from the extant literature as well as our own estimation

[3]Examples of capital adjustment costs include installation costs, costs of disrupting the old production process and fees of training staff to adapt to the new equipment. More specific examples are provided in Section 2.3.

results based on the first order condition and simulated method of moments beginning with the firm's dynamic optimization problem. The evidence of the rising trend of adjustment costs remains robust to using alternative measures of Tobin's q as well as to the estimation performed on the basis of the Euler investment equation, which circumvents the use of a proxy for q. The simulated method of moments (SMM), which chooses the parameters that match the actual moments with simulated moments, also yields consistent results.

We argue that, based on the economic literature and historical statistics, the increasing capital adjustment costs can be ascribed to the development of technology, e.g., the widespread use of computers and software, network and automated systems. According to PwC (2016), "the use of 3D printing is disrupting US manufacturing" and "the most commonly cited barriers to the adoption is the cost and lack of talent and current expertise". Factories are switching to electrical vehicles, which although brings "new ways of structuring transportation, land use and domestic energy use", requests the installations of necessary infrastructure (Barkenbus 2009). The adoption of high-tech equipment and machine tools requires specialist skills to install and operate them and makes retraining during working hours become inevitable.[4] In the chapter, we show an upsurge in the acquisition of information technology and communications equipment in production and an increasing participation rate in the training. The robustness of the relationship between the magnitude of capital adjustment costs and technological progress is subsequently demonstrated using an analysis that exploits both cross-industry and cross-country variation of the capital adjustment costs.

This work contributes to the literature on corporate investment and financing decisions in several ways. Most significantly, we demonstrate that I-CF sensitivity can capture both financial frictions as well as capital adjustment costs. Investment is reliant on cash flow when it is costly to access the external financing market but it is *less*

[4] According to Clegg (Feb 28th, 2018), the online education program funded by AT&T to retrain the workforce "requires at least 10 hours' homework a week and take 6 to 12 months to complete" and SEAT's (the Spanish car company) re-skilling program opens the possibility for employees to retrain during working hours.

sensitive to cash flow in the presence of a higher capital adjustment cost. Empirically, we show that it is the increasing magnitude of frictions generated by capital adjustment that contribute to the declining I-CF sensitivity pattern. We, therefore, highlight the role of frictions generated by the real side of economic activities in explaining the responsiveness of investment to internal funds as in contrast with the frictions generated by the financial market.

To capture the evolution of the investment-cash flow sensitivities, this chapter features uses of time-varying model parameters. In this way, it allows us to infer the time-series trend of economic parameters (most importantly, capital adjustment cost parameter). Cash flow is a source of internal funds before the firm taps the external financing market. The idea to model cash flow into investment-q equation is closest to the work of Lewellen & Lewellen (2016), which is, however, restricted to the quadratic adjustment cost. We consider a more general form of the adjustment cost function and estimate the economic parameters across each time period based on the q equation. Furthermore, we attempt to address the problem of measurement error in q by applying alternative measures of q, re-estimating the relevant parameters based on the investment Euler equation which does not require using q, and with the SMM methodology. Taken together, we present a robust evidence that the capital adjustment cost parameter is increasing over time. The linkage of model parameters with I-CF sensitivity is related to several studies for structural models (e.g., Riddick & Whited 2009, Gamba & Triantis 2008). They attempt to investigate the effect of model parameters on the cross-sectional financial and saving behavior. We, however, modify the comparison framework from cross-section to time-series and examine how the time-series variation of model parameters can explain the investment response of the firm over time.

The remainder of this chapter is structured as follows. Section 2.2 describes data sources and variables and documents the decreasing pattern of I-CF sensitivity. Section 2.3 provides develops testable hypotheses for the decrease of I-CF sensitivity based on the q model of investment. Section 2.4 presents the estimation results for the structural economic parameters and discusses how these parameters can explain the declining pattern of I-CF sensitivity. Section 2.5 contains a robustness analysis and Section 2.6 concludes.

2.2 Data set and baseline results

2.2.1 Data sources, variables and summary statistics

The data comes from all manufacturing firms (SIC between 2000 and 3999) in the Compustat industry annual file, covering the period between 1977 and 2016. (Inside parentheses, we provide the name of the relevant data item in the Compustat industry annual file.) Investment, I, is measured as capital expenditure ($capx$) for annual data from 1977-2016. Capital, K, is defined as net property, plant and equipment ($ppent$). Tobin's average q, Q, is the market value of capital over net property, plant and equipment. Market value of capital is constructed as market value of asset minus the difference between the book value of assets (at) and the book value of capital ($ppent$). Note that by subtracting the gap between total asset and physical capital, we remove the value of intangible assets in computing the market value of physical capital. This allows us to measure investment opportunities for the physical capital. The market value of assets is the sum of market value of common stock ($csho \times prcc$), total liabilities (lt), and preferred stock ($pstk$) minus deferred taxes ($txditc$). Cash flow is income before extraordinary items (ib) plus depreciation and amortization (dp). We keep the manufacturing firms which have SIC code between 2000 and 3999 and keep only firms incorporated in the U.S. Data variables, namely investment, Tobin's q and cash flow, are required to have nonmissing values for each observation. Following Almeida et al. (2004), we remove firms that have sales or asset growth exceeding 100% to eliminate the effect of business discontinuities. We drop the firms that have asset, sales or capital less than 1 million USD (see Chen & Chen (2012) and Moshirian et al. (2017)). Finally, following Hennessy & Whited (2007), we winsorize all regression variables at 2% at each tail to reduce the effect of outliers for each year.[5]

Table 2.1 provides summary statistics for the regression variables. We divide the samples into five-year subsample periods. The results are provided for each of the subsample period. The mean and median level of investment-to-capital ratio are relatively stable over time. The mean level of cash flow-to-capital ratio has decreased substantially in recent decades while the mean level of Tobin's q has risen from 1.30 to 10.82 over the 40 years. The median level of cash flow-to-capital ratio remains relatively steady while the median level of Tobin's q has increased over time as well. Both 25th percentile and 75th percentile of Tobin's q are increasing over time too, which suggests that the increase of Tobin's q is not limited to the sample of value firms or growth firms. There is considerable variance in Tobin's q and cash flow-to-capital ratio in the recent periods as indicated by their great dispersions between 25th percentile and 75th percentile and large standard deviations. We also present serial correlation coefficients of the regression variables. The serial correlation (see Section 2.3 for details) of investment-to-capital ratio indicates the smoothness of investment behavior and it rises from around 0.45 in 1980s to 0.57 in the recent periods. The q variable is also highly autocorrelated, which can result in the use of lagged instrumental variable to correct for the measurement error in q being somewhat problematic (Almeida et al. 2010, Erickson & Whited 2012).

2.2.2 Baseline regression results and time-series variation of I-CF sensitivity

The baseline regression equation for investment is:

$$\frac{I_{it}}{K_{it}} = \beta_0 + \beta_1 Q_{it} + \beta_2 \frac{CF_{it}}{K_{it}} + \eta_i + \eta_t + \varepsilon_{it}$$

[5] To reduce measurement error in the construction of q, Gilchrist & Himmelberg (1995) keep the observations that have Tobin's q between 0 and 10. We mitigate the impact of measurement error in q by winsorizing the regression variables at a higher level. Appendix F also provides the baseline regression results and nonlinear estimation results of q equations with data with no winsorization as a robustness check.

Table 2.1: Summary statistics for regression variables

This table displays summary statistics for the main regressor variables. It reports mean, standard deviation, percentiles and first-order serial correlation for investment to capital ratio, cash flow to capital ratio and Tobin's q for each five-year subsample period from 1977 to 2016. All firm-level data are collected from Compustat over 1977-2016 period. The sample contains all manufacturing firms (SIC code between 2000 and 3999) in U.S.. I/K is the firm's capital expenditure, scaled by beginning-of-period net property, plant and equipment. CF/K is firm's internal cash flow (income before extraordinary items plus depreciation), deflated by beginning-of-period net property, plant and equipment. Q is Tobin's average q in the beginning of period, which is market value of capital over book value of capital (measured by net property, plant and equipment).

	Mean	Std. Dev.	Percentiles			Serial
			25th	50th	75th	Corr.
Sample period:1977-1981						
I/K	0.284	0.202	0.150	0.233	0.350	0.473
Q	1.296	1.788	0.321	0.812	1.679	0.830
CF/K	0.415	0.324	0.234	0.376	0.559	0.770
Sample period:1982-1986						
I/K	0.257	0.212	0.119	0.198	0.320	0.410
Q	2.426	3.141	0.704	1.370	2.893	0.762
CF/K	0.302	0.435	0.134	0.294	0.495	0.680
Sample period:1987-1991						
I/K	0.235	0.180	0.114	0.190	0.298	0.464
Q	2.929	3.844	0.889	1.672	3.351	0.798
CF/K	0.270	0.587	0.108	0.280	0.490	0.624
Sample period:1992-1996						
I/K	0.266	0.225	0.119	0.198	0.331	0.541
Q	4.860	7.032	1.142	2.320	5.286	0.781
CF/K	0.329	0.858	0.136	0.326	0.600	0.639
Sample period:1997-2001						
I/K	0.258	0.221	0.111	0.192	0.327	0.482
Q	6.204	10.435	1.139	2.571	6.409	0.686
CF/K	0.086	1.301	0.009	0.286	0.585	0.631
Sample period:2002-2006						
I/K	0.220	0.207	0.090	0.156	0.274	0.524
Q	8.730	15.224	1.328	3.339	8.783	0.713
CF/K	0.049	1.769	-0.012	0.306	0.686	0.688
Sample period:2007-2011						
I/K	0.231	0.209	0.097	0.170	0.289	0.508
Q	8.867	15.466	1.329	3.479	9.140	0.760
CF/K	0.031	2.113	-0.055	0.343	0.799	0.660
Sample period:2012-2016						
I/K	0.236	0.192	0.114	0.184	0.287	0.570
Q	10.816	20.212	1.552	3.963	10.430	0.829
CF/K	0.070	2.274	0.094	0.389	0.823	0.765

where $\frac{I_{it}}{K_{it}}$ is firm's physical investment scaled by beginning-of-period capital, $\frac{CF_{it}}{K_{it}}$ is firm's cash flow deflated by beginning-of-period capital, Q_{it} is the beginning-of-period Tobin's q, which is a proxy for investment opportunities, η_i denotes the firm-specific fixed effect and η_t is the year fixed effect. $\beta_i, i \in \{0, 1, 2\}$ denotes the relevant regression coefficient.

Table 2.2 presents regression results from 1977-1981 to 2012-2016. Investment-cash flow sensitivity, as defined in the empirical literature, is cash flow coefficient (β_2). In period 1977-1981 it equals 0.283 and is statistically significant. Afterwards, I-CF sensitivity decreases. In 2002-2006, I-CF sensitivity becomes statistically insignificant and remains so in period 2007-2011. It becomes statistically – but not economically – significant again in 2012-2016.

Ağca & Mozumdar (2008) argue that the declining trend of I-CF sensitivity can be explained by the decreasing financial constraints as indicated by the rising fund flows, the increasing number of analyst following, the number of firms with bond rating and the increasing proportion of large institutional ownership. Nonetheless, Chen & Chen (2012) show that I-CF sensitivity still decreases even for financially unconstrained firms and there is no sign of loosening financial constraints as the volume of new external financing remains relatively stable.

2.3 Capital adjustment costs and I-CF sensitivity

The extant literature on investment-cash flow sensitivity has largely focused on the effects of financial constraints (e.g., Ağca & Mozumdar 2008, Chen & Chen 2012). Yet, relatively little effort has been made to investigate the impact of capital adjustment costs on the responsiveness of investment to additional cash flow. For instance, the presence of convex adjustment costs results in only a partial adjustment of capital towards its desired level and leads to a positive serial correlation of investment (see, e.g., Cooper et al. 1999, Caballero & Engel 2003). Although Cooper & Haltiwanger

Table 2.2: Baseline linear regression result

This table reports estimation results from baseline linear regression model

$$\frac{I_{it}}{K_{it-1}} = \beta_0 + \beta_1 Q_{it-1} + \beta_2 \frac{CF_{it}}{K_{it-1}} + \eta_i + \eta_t + \varepsilon_{it},$$

in each five-year subsample period. η_i captures firm-specific fixed effect and η_t captures year fixed effect, $\frac{I_{it}}{K_{it-1}}$ is the firm's capital expenditure, scaled by beginning-of-period net property, plant and equipment, $\frac{CF_{it}}{K_{it-1}}$ is firm's internal cash flow (income before extraordinary items plus depreciation), deflated by beginning-of-period net property, plant and equipment, Q_{it-1} is firm's Tobin'q in the previous year, which is market value of capital over book value of capital (measured by net property, plant and equipment. β_1 denotes coefficient on q and β_2 denotes cash flow coefficient. Standard errors are clustered at firm level and reported in the parenthesis. Adjusted R square R_a^2 and number of observations are also reported. The sample contains all manufacturing firms collected from Compustat over 1977-2016 period. ***, **, *indicate significance at the 1%, 5% and 10% levels. Difference (and corresponding q value) is computed as the difference in coefficients between 1977-1981 and 2012-2016.

Period	β_0	β_1	β_2	R_a^2	Obs
1977-1981	0.125***	0.023***	0.283***	0.488	8005
	(0.009)	(0.003)	(0.019)		
1982-1986	0.134***	0.023***	0.135***	0.437	8057
	(0.008)	(0.003)	(0.014)		
1987-1991	0.137***	0.016***	0.065***	0.44	7768
	(0.006)	(0.002)	(0.008)		
1992-1996	0.188***	0.012***	0.053***	0.542	8412
	(0.007)	(0.001)	(0.007)		
1997-2001	0.151***	0.008***	0.027***	0.478	8736
	(0.006)	(0.001)	(0.005)		
2002-2006	0.2***	0.006***	0.006	0.526	7556
	(0.007)	(0.001)	(0.004)		
2007-2011	0.169***	0.007***	-0.0001	0.498	6487
	(0.007)	(0.001)	(0.004)		
2012-2016	0.207***	0.005***	0.005***	0.553	5151
	(0.004)	(0.000)	(0.002)		
Difference	-0.082	0.018	0.278		
p-value	0.203	0.000	0.000		

(2006) reports that the serial correlation of investment is low (estimated at 0.058) at the plant-level, we show that the serial correlation is non-trivial at the firm-level (see Table 2.1). To further support the presence of the convex adjustment costs (as compared with the fixed costs), we allow the function of capital adjustment costs to take a more general form and test for its convexity in Section 2.4.

A capital adjustment cost is the expenditure incurred before the equipment or plant can be put to full use and it comprises installing costs (e.g., loss in production during installation), fees of training labor to accommodate the new capital, lost expertise due to the adoption of new technology, overtime costs, costs of disrupting the old system and reorganising the production process. Goolsbee & Gross (1997) report that adjustment costs for airline industry are mainly related to set-up costs in order to match the new fleet and fees of training personnel to fly and maintain the fleet. Kiley (2001) assert that adjustment costs of high-tech equipment, such as the costs of training workers to use the technologies and reorganizing activities associated with the installation of new capital, are important. Here are examples of capital adjustment costs extracted from the company reports. Nestlé Group (2016, p16) has expensed the costs of disruption as "impairment of property, plant or equipment", which are mainly concerned about "the plans to optimise industrial manufacturing capacities by closing or selling inefficient production facilities" and the expenses amount to 201 million of CHF. Equipment and facilities used for manufacturing are undergoing a costly technological change. According to Intel Corporation (2016, p36), their R&D spending has increased by 5% in 2016 from 2015 and a significant part of the rise comes from the high development costs for the new process technology and manufacturers of semiconductors are now facing "the increased costs of constructing new fabrication facilities to support smaller transistor geometries". From the perspective of sustainability, costs may incur to meet the high environmental standards when building existing plants or constructing new sites.

If firms had an unrestricted access to external finance market, they could invest whenever valuable projects arise and internal funds would be irrelevant. With a limited access to the external capital market, the sensitivity of investment on cash flow is positive and does not only depend on the costs of obtaining outside financing, but also on the costs of adjusting the capital level. Financially constrained firms will boost their investment to a smaller extent upon receiving cash windfall when capital adjustment is costly. In this section, we formulate specific predictions on how external financing costs and adjustment costs affect I-CF sensitivity and provide evidence supporting the link between the trend of I-CF sensitivity and the intertemporal evolution of capital adjustment costs.

Assume that time is discrete, I_t is investment at time t, K_t is capital stock that satisfies the standard intertemporal condition

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

with $\delta \geqslant 0$ denoting the depreciation rate. The adjustment cost, $G(I,K)$, depends on both investment and installed capital. The unit price of output and price of capital goods are assumed to be 1. To operationalize the notion of the adjustment cost, we assume that

$$G(I,K) = \frac{1}{\psi}\gamma(\frac{I}{K})^{\psi}K,$$

where $\gamma > 0$ and ψ reflects the elasticity of adjustment cost to investment rate. ψ equals 2 in a model with a quadratic adjustment cost. The assumption of a quadratic adjustment cost is essential in delivering the linear baseline regression. By allowing the adjustment cost function to take a more general form, we can provide a test for the functional form of capital adjustment cost function, specifically the test of $\psi = 2$.[6] $\Pi(A,K) = AK^{\alpha}$ denotes profit function and A is the stochastic profitability shock that determines the exogenous state of the firm and α is the curvature on the profit function (in Appendix 2.A, we derive the form of the profit function). As in Gomes (2001) and Cooper & Ejarque (2003), we consider cash flow as a means to

[6] We empirically verify whether this assumption is plausible in Section 2.4. If the adjustment cost function is quadratic, an additional \$1 of investment will lead to a \$$\gamma\frac{I}{K}$ increase in capital adjustment costs.

supply firms with internal funds to finance investment. (We also present a model in a prefect capital market in Appendix B, where we show that cash flow is added to the empirical regression in an ad hoc way in the frictionless model.) The way to model financial constraints is generally complex and we do not attempt to to endogenize financial policy along the lines of Li, Whited & Wu (2016). As we are only interested in comparing the magnitude of the financial frictions over time, we simply impose a form for external financing cost as Gomes (2001) and Cooper & Ejarque (2003) do. $H(X, K)$ is external financing cost function where X is the amount of external financing funds one needs to raise to meet its investment demand (cash flow shortfall). We assume equity is the sole source of financing and is only issued when the firm is not able to fund the investment with its internal cash flow. Hennessy & Whited (2007) argue that cost of external equity decreases with size of firm, hence external financing cost is a function of capital K, whereas Krasker (1986) finds that shadow cost of equity increases with the number of shares issued, hence external cost function is assumed to convex and quadratic. We assume that the form for external financing cost function $H(X, K)$ is

$$H(X, K) = \frac{1}{2} b\Phi(\frac{X}{K})^2 K.$$

As in Cooper & Ejarque (2003), the amount of external financing funds X is defined as the gap between investment and cash flow. We can include capital adjustment costs in calculating X but we do not do in order to simplify the equations and also including them does not substantially affect the main results. Cash flow is the profit generated by the capital in place, and hence $X = I - \Pi$. Φ is an indicator which is equal to one if $I \geqslant \Pi$ and zero otherwise. Parameter b reflects the cost of external financing. Fazzari et al. (1988) characterize financial constraints as the wedge between the cost of internal capital and the cost of accessing external capital. The higher the cost embedded in raising funds from outside capital market (such as information asymmetric costs in Myers & Majluf 1984), the higher the degree of financial constraints.

Equity holders choose an investment policy to maximize the firm value taking into account the cost of external financing

$$V(A_t, K_t) = \max_{I_t}[(\Pi(A_t, K_t) - I_t - G(I_t, K_t) - H(X_t, K_t)) + \theta E_{A_{t+1}|A_t} V(A_{t+1}, K_{t+1})],$$

where θ denotes the discount factor. The marginal Tobin's q (denoted subsequently by q_t) is defined as $\theta E_{A_{t+1}|A_t} V_K(A_{t+1}, K_{t+1})$, where $V_s(A, K)$ denotes the partial derivative of firm value V with respect to $s \in \{A, K\}$. The first order condition with respect to I, which equates marginal return with marginal cost of investment, yields the following q equation:

$$1 + \gamma \left(\frac{I_t}{K_t}\right)^{\psi - 1} + b\Phi \left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t}\right) = q_t. \tag{2.3.1}$$

Based on the q equation, we can derive the partial derivative of investment with respect to cash flow

$$\frac{\partial I/K}{\partial \Pi/K} = \frac{b\Phi}{\gamma(\psi - 1)(\frac{I}{K})^{\psi - 2} + b\Phi}. \tag{2.3.2}$$

See Appendix 2.C for details of the derivation. Provided that $\gamma > 0$, lower b is associated with a more muted response of investment relative to cash flow. As it is possible that the decreasing I-CF sensitivity is the result of declining financing cost parameter, we formulate the following empirical prediction:

H1: *Cash flow sensitivity of investment decreases as a result of lower costs of external financing.*

From (2.3.2), we obtain that γ is negatively related to the partial derivative of investment with respect to cash flow. In Appendix E, we also derive the equations for the firm values considering a fixed capital adjustment cost based on Whited (2006). It provides a framework in which the a fixed capital adjustment cost can lead to a similar negative relationship between capital adjustment cost and I-CF sensitivity. This result can be explained as follows. If the firm is financially constrained, its investment depends on the availability of internal funds. But this dependence becomes weaker with a higher adjustment cost as the firm is not willing to increase capital upon receiving one unit of cash flow when making such capital adjustment is costly. Therefore, an alternative explanation for the decreasing I-CF sensitivity over time could be the gradually increasing adjustment costs. Hence, we formulate the second empirical prediction:

H2: *Cash flow sensitivity of investment decreases due to higher capital adjustment costs.*

The above discussion implies that the changes in I-CF sensitivity may be a joined result of the evolution of both financing constraints as well as capital adjustments costs. What is worth pointing out is that the imperfections on the real side of firm's activities (adjustment costs) have an opposite effect on this sensitivity compared to imperfections from financial markets (financing constraints).

Similarly, we can also obtain the partial derivative of investment with respect to q

$$\frac{\partial I/K}{\partial q} = \frac{1}{\gamma(\psi - 1)(\frac{I}{K})^{\psi-2} + b\Phi}. \tag{2.3.3}$$

One can see from (2.3.3) that partial derivative of investment to q is inversely related to both capital adjustment costs and financial frictions. The investment demand will vary less with the growth opportunities reflected in q if the firm's investment behavior is constrained by frictions from either financial market or from real economic activities. With that in mind, we offer a preliminary test of our predictions by looking at the time trend of investment-q (I-q) sensitivity. If I-CF sensitivity declines alongside with the decrease of financial constraints, we should observe an increasing trend for q sensitivity. On the other hand, if I-CF sensitivity declines as a result of higher capital adjustment costs in late years, we should observe a decreasing trend for I-q sensitivity as well.

The baseline OLS regression results in Table 2.2 indicate both a declining q sensitivity of investment as well as a downward-sloping I-CF sensitivity. This combination of results supports the second prediction that decreasing I-CF sensitivity is driven by the rising capital adjustment costs. Nonetheless, the OLS estimators are potentially biased when the independent variables (right-hand-side variables) such as q variable are measured with an error (e.g., Erickson & Whited 2000, 2012, Almeida et al. 2010). Therefore, in Sections 2.4 and 2.5 we provide a set of more refined tests of our predictions to assess the evolution of capital adjustment cost and financial frictions.

2.4 Empirical evidence

2.4.1 Empirical implementation of q equation

A. Estimation results with Tobin's q

In the baseline regression equation, cash flow is added to the investment-q equation in an *ad hoc* way and, therefore, little is said about the relationship between this economic parameter and I-CF sensitivity. Even though Abel & Eberly (2011) provide theoretical micro-foundations for the existence of I-CF sensitivity, they do so under strong assumptions of no capital adjustment costs and a sufficient time-series variation in the drift rate of productivity. Lewellen & Lewellen (2016) attempt to relate economic parameters with I-CF sensitivity, but their approach is subject to a number of potential shortcomings. First, they infer parameters based on the baseline linear regression, which brings the cash flow to right hand side on purpose, rather than bear the estimation on the optimality condition that equates the marginal value of capital with its marginal cost (q equation). The baseline regression regards q variable, which is always measured with error, as the explanatory variable. Based on the classical measurement error theory, this will lead to inconsistency however independent the measurement error is. One could also find that implying economic parameters from the baseline regression coefficients will result in implausibly large estimates for the adjustment cost and financing cost parameters. Second, they adopt an ex ante assumption of a quadratic adjustment cost. We relax the assumption of the quadratic adjustment cost and provide estimates of model parameters based on the q equation, which comes directly from the first order condition. In such a context, we let q variable become the dependent variable such that the measurement error in q will not infect the parameter estimates as long as the measurement error is independent of investment and cash flow.

We start by estimating the model parameters based on the q equation.[7] The corresponding estimation equation of (2.3.1) is

$$Q_{it-1} = 1 + \gamma \left(\frac{I_{it}}{K_{it-1}} \right)^{\psi - 1} + b\Phi \left(\frac{I_{it}}{K_{it-1}} - \frac{CF_{it}}{K_{it-1}} \right) + \eta_t + \eta_j + \varepsilon_{it}, \tag{2.4.1}$$

η_t captures year fixed effect and η_j is dummy variable for each two-digit SIC industry level. [8] Other variables are as those described in Section 2.2.1. Estimated parameters are b, ψ and γ and they should all be positive. We select the set of parameters that produce the least sum of squared error $\sum \varepsilon_{it}^2$ (nonlinear least squares estimation). We present the estimation results in Panel A of Table 2.3.

As discussed above, we choose mismeasured q variable as the dependent variable, which will *not* lead to inconsistencies as long as the measurement error is independent of the explanatory variables.[9] Therefore, the estimates of the parameters based on the q equation that has q as the regressand fare better than the ones implied from the reciprocal of β_1 and the ratio of β_2 and β_1. The adjusted R^2 shown in Column 5 of Panel A Table 2.3 reveals that the model goodness-of-fit improves over time. It's

[7]Even though it is may be more accurate to infer relevant parameters by matching the moments from a dynamic structural model that endogenizes a firm's investment policy to the moments observed in the sample, it is helpful first to understand the intuition about how model parameters affect I-CF sensitivity by looking at the partial derivative of investment with regard to cash flow derived from the q equation. (In a more complex model of firm dynamics, such as Hennessy & Whited (2007), it is generally not possible to obtain a closed-form expression for the I-CF relationship.) Later, we provide the parameters estimates based on the structural methods of moments in Section 2.4.3

[8]We use industry dummies instead of firm dummies out of the concern for the limited memory of the computer. Moreover, it is reasonable to aggregate short panel data in a higher level as regression may fail to capture the characteristics of firms who have single observation during the five-year subsample period if one uses firm-specific fixed effect. (See discussions in Lewellen & Lewellen (2016) about the reluctance to add firm fixed effect.) We find that between 10%-17% of the firms have single observation and around 30% of the firms have only two-year observations in the subsample period.

[9]In Erickson & Whited (2000), measurement error is assumed to be independent of $\frac{I}{K}$ and $\frac{CF}{K}$. Error that causes the deviation between marginal q and average q such as market power and interest rate might be considered as exogenous. Even if the measurement error in not independent, the biases induced by the measurement error in the explained variable can be translated into omitted variable biases. The factor variables that cause empirical average q to deviate from marginal q is regarded as omitted variables. Therefore, one can deal with the measurement error by incorporating into the estimation equation the factor variables that could possibly cause such difference between empirical average q and marginal q. We find that the parameter estimates including factor variables do not change too much.

worth noting that the right-hand side in the q equation implies the true marginal q based on the first order condition. Therefore, the R^2 of the q equation, based on the definition in Erickson & Whited (2000), can roughly recover the proxy quality of empirical q. The R^2 is increasing over time, which is consistent with the finding in Chen & Chen (2012) that the measurement quality in Tobin's q is improving.

The estimates of ψ are reported in Column 3 of Panel A Table 2.3 and they are all significantly different from (larger than) zero, which justifies the convex form (as compared to the fixed form) of capital adjustment costs function. Column 6 in Panel A of Table 2.3 presents the t statistics under the null hypothesis that $\psi = 2$. Most of the estimates of ψ are not significantly different from 2 at the 1% significance level, which yields support for the commonly used quadratic cost assumption. Hence, for simplicity, we from now on assume a quadratic function for capital adjustment costs.

The parameter b, which measures the cost of external financing, reflects the degree of financial constraints and its estimates are reported in Column 4 of Panel A, Table 2.3. It is significantly positive in most of the periods even though it is zero in 1977-1981.[10] The estimated b is much higher in late 2000s than in the earlier days. If one interpreters I-CF sensitivity as a measure of financial constraints, one would expect a declining b over time. The degree of financial constraints, as implied by b, is increasing across periods. This is consistent with Chen and Chen's (2012) evidence that financial constraints are *not* loosening over time. Also, studies such as Almeida, Campello & Weisbach (2004) and Faulkender & Wang (2006) argue that constrained firms are more inclined to hold cash and Bates, Kahle & Stulz (2009) show that there is an increase in cash holding of U.S. firms. Therefore, we reject the first prediction and conclude that financial constraints cannot explain the decreasing trend of I-CF sensitivity.

The estimates of adjustment cost parameter γ, which are reported in Column 2 of Panel A Table 2.3, fluctuate around 5 in early years and increase to around 15 in

[10]This is not surprising as we do not include cash savings into the funding gap, thereby b measures the combined costs of using external equity funds and spending out of cash, which is assumed to be costless.

1990s and 25 in 2000s. The rising trend of adjustment cost parameter might explain the phenomenon that I-CF sensitivity declines over time. Investment responds less strongly to cash flow in late periods because making capital adjustment is more costly. With respect to the magnitude of γ, a few studies, which tend to infer the adjustment cost parameter from the reciprocal of the q coefficient, yield implausibly high estimates for γ. For example, Gilchrist & Himmelberg (1995) obtain a γ as high as 20 during 1985-1989. Hayashi (1982), using data from 1952-1978, also obtains a γ as large as 20. The adjustment cost parameter estimated in this setting is much tighter and plausible, i.e., γ is shown to be around 5 in 1977-1991, which is almost four times lower. As stock-market-based Tobin's average q is considered as less reliable in measuring the investment opportunities (e.g., Cummins, Hassett & Oliner 2006, among others), we intend to supply further empirical evidence of the increasing magnitude of capital adjustment costs in the following sections.

B. Estimation results with alternative measures of q

Average q (market-to-book capital ratio) is not a good proxy for marginal q if any of the linear homogeneity assumptions in Hayashi (1982) collapses. To address the concern that the estimated rising trend of adjustment costs is driven by the imperfect proxy for marginal q, we rerun the estimation with alternative measures of q. Gala (2014) proposed a state-space measure of marginal q using capital stock and profitability shock. He provides the estimates for the curvature on the profit function, which is $\alpha = 0.51$, and hence profitability shocks can be implied from net profit as $A = \Pi/K^{\alpha}$. Average q (market-to-book capital ratio) is denoted as Q. After we run the regression of $log(Q) = a_0 + a_1 log(A) + a_2 log(K) + a_3 log(A)^2 + a_4 log(K)^2 + a_5 log(A) log(K) + \varepsilon$ in each subsample period, we can obtain the fitted value for $\widehat{log(Q)}$ or $\hat{Q}$ and coefficient sets for capital stock and profitability shock. Marginal q can be written as $q = \frac{\partial V}{\partial K} = \frac{V}{K}\left(1 + \frac{\partial log(Q)}{\partial log(K)}\right)$ and hence one can compute marginal q by $q = \widehat{Q}(1 + \hat{a}_2 + 2\hat{a}_4 log(K) + \hat{a}_5 log(A))$.

In standard investment theory, marginal q is based on managers' evaluation of firm's fundamentals and any deviations of market valuations from managers' assessed fundamentals will be regarded as "misvaluation"(Blanchard, Rhee & Summers 1993). To alleviate the concern that the parameter estimates are confounded by the misvaluation component, we follow Goyal & Yamada (2004) and Campello & Graham (2013) and construct fundamental q as the component in the market-to-book ratio that can be explained by observable fundamental variables, which are the lagged value of cash flow-to-capital ratio, sales growth, current asset-to-capital ratio, debt-to-capital ratio, capital spending, capital expenditure, size (market capitalization), industry sales growth, industry capital investment growth and industry R&D growth. Finally we repeat the nonlinear estimation with Gala's marginal q and fundamental q and then present the results in Panel B of Table 2.3.

The results with Gala's q (reported in the left panel of Panel B Table 2.3) reveal that the estimates of the adjustment cost parameter γ rise across periods from 0.029 in 1977-1981 to 4.782 in 2012-2016. The results with fundamental q (reported in the right panel of Panel B Table 2.3) also show that the adjustment cost parameter γ increases steadily over time. We assume a quadratic form of adjustment cost function in both cases given that ψ shown in Panel A does not significantly differ from 2 in economic magnitude. Both measures demonstrate that the financing cost parameter is increasing through time. We conclude that the increasing trend of adjustment cost parameter is robust even if we replace the market-to-book ratio with the alternative proxies for q variable.

Table 2.3: Estimation of q equation

The estimation in Panel A is conducted based on (2.5) in each five-year subsample period where Q_{it-1} is defined as firm's Tobin's average q. b is external financing cost parameter. γ is adjustment cost parameter. ψ measures the elasticity of adjustment cost. $\psi = 2$ if the adjustment cost function is quadratic. Φ is indicator which is equal to one when firms seeks external financing and zero otherwise. Column 6 in Panel A reports t statistics under the null hypothesis that $\psi = 2$. The estimation in Panel B assumes quadratic structure of adjustment cost and estimates parameters using alternative measures of q variable. Q_{it-1} is defined as Gala's marginal q in the left panel and is fundamental q in the right panel. Adjusted R square R_a^2 in both Panel A and Panel B is one minus mean squared error divided by the variance of Q_{it-1}. Robust (clustered at industry level) standard errors for each parameter are reported in parenthesis. ***, **, *indicate significance at the 1%, 5% and 10% levels.

Panel A: Estimation of q equation with Tobin's q

Period	γ	ψ	b	R_a^2	$t(\psi = 2)$
1977-1981	2.662***	2.233***	0	0.223	1.894
	(0.378)	(0.123)	(0.340)		
1982-1986	5.459***	2.068***	0.25	0.241	1.193
	(0.371)	(0.057)	(0.267)		
1987-1991	6.646***	2.237***	0.904***	0.176	2.326
	(0.117)	(0.102)	(0.294)		
1992-1996	12.313***	2.083***	2.378***	0.276	1.976
	(0.035)	(0.042)	(0.235)		
1997-2001	16.904***	1.87***	2.061***	0.254	-2.500
	(0.773)	(0.052)	(0.391)		
2002-2006	30.174***	2.164***	2.528***	0.349	5.655
	(1.681)	(0.029)	(0.219)		
2007-2011	27.486***	2.341***	2.344***	0.321	3.707
	(2.016)	(0.092)	(0.911)		
2012-2016	30.9672***	2.0368***	3.844***	0.367	2.017
	(0.038)	(0.018)	(0.181)		

Panel B: Estimation of q equation with alternative measures of q

	Gala's marginal q:			Fundamental q:		
Period	γ	b	R_a^2	γ	b	R_a^2
1977-1981	0.029	0	0.0495	1.151***	0	0.1344
	(0.222)	(0.108)		(0.340)	(0.120)	
1977-1981	0.231	0.144*	0.0452	1.439***	0	0.1383
	(0.373)	(0.470)		(0.703)	(0.754)	
1987-1991	0.418	0.198	0.004	2.275***	0	0.1337
	(0.339)	(0.663)		(0.750)	(1.283)	
1992-1996	0.941	0.549	0.0067	3.676*	0	0.1657
	(1.054)	(0.966)		(2.014)	(0.743)	
1997-2001	1.541***	0.091	0.121	3.556	0.182	0.1092
	(1.336)	(0.142)		(3.316)	(0.434)	
2002-2006	2.693*	0.218	0.0155	9.209***	0.016	0.1414
	(1.603)	(0.163)		(4.297)	(0.560)	
2007-2011	3.848*	0.246	0.0998	9.411***	0.900	0.2029
	(2.008)	(0.233)		(4.146)	(0.916)	
2012-2016	4.782 ***	0.178	0.1825	8.494**	1.102	0.2023
	(2.240)	(0.209)		(4.627)	(1.301)	

2.4.2 Empirical implementation of Euler equation

The investment Euler equation provides an additional approach to estimating economic parameters of interest. The Euler equation, which equates the marginal cost of investment today with the expected discounted cost of waiting to invest tomorrow, has the advantage of avoiding the use of the q variable. Assuming a risk-free discount rate (denoted by r), the value of firm is

$$V(A_t, K_t) = \max_{\{K_{\tau+1}, I_\tau\}_{\tau=t}^{\infty}} E_t \sum_{\tau=t} (\frac{1}{1+r})^{\tau-t} (\Pi(A_\tau, K_\tau) - I_\tau - G(I_\tau, K_\tau) - H(X_\tau, K_\tau)),$$

subject to $K_{t+1} = I_t + (1-\delta)K_t$.

We assume a quadratic form for the adjustment cost function and linear homogeneity for profit function as in Gomes, Yaron & Zhang (2006). Differentiating with respect to K_{t+1} and adding an expectation error ϵ_{t+1} where $E_t(\epsilon_{t+1}) = 0$ to remove the expectation operator, we arrive at the estimation equation for the Euler equation (Details for derivation can been seen in Appendix 2.D):

$$\begin{aligned}
&\frac{1}{1+r}\Big[(1-\delta)\left(1 + \gamma\left(\frac{I}{K}_{t+1}\right) + b\phi\left(\frac{I}{K}_{t+1} - \frac{\Pi}{K}_{t+1}\right)\right) + \\
&\frac{\Pi}{K}_{t+1} + \frac{1}{2}\gamma\left(\frac{I}{K}_{t+1}\right)^2 + \frac{b}{2}\phi\left(\frac{I}{K}_{t+1} - \frac{\Pi}{K}_{t+1}\right)\left(\frac{I}{K}_{t+1} + \frac{\Pi}{K}_{t+1}\right)\Big] + \epsilon_{t+1} \\
&= 1 + \gamma\left(\frac{I}{K}_t\right) + b\phi\left(\frac{I}{K}_t - \frac{\Pi}{K}_t\right).
\end{aligned} \tag{2.4.2}$$

We follow Whited (1998) and employ two-step GMM to estimate the parameters in (2.4.2). Any information set at time t is orthogonal to the expectation error at time $t+1$. Therefore, we use GMM to estimate the parameters with the moment condition of $E(Z_t\epsilon_{t+1}) = 0$ where Z_t denotes a set of instruments. The instrument set consists of time dummy variables, lagged value of investment-capital ratio, cash flow-capital ratio, debt-capital ratio, current asset-capital ratio, capital spending, sales growth and cash reserve. The estimation results are provide in Table 2.4. The J statistic and its corresponding p value provide an overview on the model's ability to fit the data. The J test shows that the overidentifying restrictions are rejected in most of the periods, which is not surprising due to the large cross-sectional variations in the dataset (see the discussion in Gomes et al. (2006)). The J statistic decreases over time, which shows that there is an improvement in the model's goodness-of-fit. The adjustment cost parameter estimates oscillate around zero in the early periods and go up to around 9 in 2010s. The estimation results based on the Euler equation reinforce the argument that the adjustment costs exhibit an increasing trend, which can justify the decreasing pattern of I-CF sensitivity.

Table 2.4: Estimation of investment Euler equation

The following table presents the two-step GMM estimation results of (2.6). The instrument sets consist of time dummy variables, lagged value of investment-capital ratio, cash flow-capital ratio, debt-capital ratio, current asset-capital ratio, capital spending, sales growth and cash reserve. The weighting matrix in the first step is identity matrix and the weighting matrix for the second step is the inverse of robust standard errors clustered at firm level. Standard errors clustered at firm level for the estimated coefficients are reported in the parenthesis. The J statistics and the corresponding p value (reported in parenthesis) are recorded in the last column.

Period	γ	b	J Stats
1977-1981	0.512***	0.000	428.831
	(0.078)	(0.208)	(0.000)
1982-1986	-0.190***	0.000	379.892
	(0.055)	(0.098)	(0.000)
1987-1991	1.453***	0.000	23.602
	(0.128)	(0.089)	(0.008)
1992-1996	-0.228***	0.685***	86.296
	(0.168)	(0.114)	(0.000)
1997-2001	1.507***	0.192***	28.849
	(0.181)	(0.063)	(0.001)
2002-2006	1.412***	0.465***	52.473
	(0.439)	(0.082)	(0.000)
2007-2011	6.856***	0.327***	21.133
	(0.660)	(0.060)	(0.020)
2012-2016	8.995***	0.717***	12.381
	(1.728)	(0.130)	(0.260)

2.4.3 Evidence based on structural estimation of parameters

2.4.3.1 Constant adjustment cost parameter

In this section, we estimate relevant parameters with simulated method of moments (SMM). SMM does not require a proxy for q and avoids the arbitrary choice of instruments in the estimation of the Euler equation. More specifically, we attempt to simulate data based on the investment-q model. The functional form of the profit, adjustment costs and financing costs are as described in Section 2.3. Subsequently, we choose the parameters that closely track the relevant properties of the actual data, which are the coefficients of the baseline regression. The key parameter of interest is capital adjustment cost parameter (γ) and we also take into account the curvature of the profit function (α), which is informative about the returns to scale in the production function and the average productivity. Also as pointed out by Cooper & Ejarque (2003), due to the concavity in the profit function, Tobin's average q is not a sufficient statistic and this concavity will affect the measurement error in Tobin's q and, thereby, the responsiveness of investment to the information content contained in cash flow. We first assume that managers are myopic and γ is perceived as constant. In each five-year subsample period, we estimate the relevant model parameters, namely γ and α, by matching the actual moments with the moments generated from the simulated data. The moments we aim to match are q sensitivity of investment, β_1, and cash flow sensitivity of investment, β_2.

The vector (A, K) defines the state of the firm and the equity holders choose the optimal investment to maximize the firm value. The source of uncertainty comes from the productivity shock of the firm A. Numerical solutions for the firm value and investment decision is based on an iterative algorithm (value iteration). To simplify notation, denote x_t as x and x_{t+1} as $x^{'}$. The logarithm of this shock variable, defined as $a = log(A)$, is assumed to follow a first-order autoregressive process with zero drift:

$$a^{'} = \rho_a a + \epsilon^{'},$$

where ρ_a is an autoregressive coefficient and $\epsilon^{'} \sim N(0, \sigma_a)$, identically independently distributed across time. We transform the first-order autoregressive process into a discrete-state Markov chain following Tauchen (1986) where the value sets and corresponding transition probability are determined by $[\rho_a \ \sigma_a]$. We let a take $N_a = 10$ points from the discretized set of $[-3\sigma_a/\sqrt{(1-\rho_a^2)} \quad 3\sigma_a/\sqrt{(1-\rho_a^2)}]$ and define the interval between each point as $w = 6\sigma_a/(\sqrt{(1-\rho_a^2)}(N_a - 1))$. We denote the probability that log stochastic shock $a^{'}$ becomes $\bar{a}_i$ given that log stochastic variable in the last period a is $\bar{a}_j$ as $p(j,i) = \Pr[a^{'} = \bar{a}_i | a = \bar{a}_j]$. Then probability matrix for $j = 1 \ldots N_a$ and $i = 1 \ldots N_a$ is,

$$\begin{aligned} p(j,i) &= \Pr[\bar{a}_i - w/2 \leqslant \rho_a \bar{a}_j + \epsilon^{'} \leqslant \bar{a}_i + w/2] \\ &= N(\frac{\bar{a}_i - \rho_a \bar{a}_j + w/2}{\sigma_a}) - N(\frac{\bar{a}_i - \rho_a \bar{a}_j - w/2}{\sigma_a}). \end{aligned}$$

The discretized set for capital stock K is defined as:

$$\bar{K}, \bar{K}(1-\delta), \ldots, \bar{K}(1-\delta)^{49},$$

where the maximum value of capital $\bar{K}$ is determined by $\Pi(\bar{A}, \bar{K}) = \delta \bar{K}$ where the profit function is $\Pi(A, K) = AK^{\alpha}$ (see Gomes (2001)). The rest of the parameter choices are close to those in Gomes (2001) and Hennessy & Whited (2007). We set autoregressive coefficient ρ_a to be 0.65 and σ_a to be 0.15. The financing cost parameter b is set to be 0.0002. The depreciation rate is set equal to 0.15 and risk-free rate is 0.05.

The procedure for estimation is as follows: For a given set of parameters $\Theta = [\gamma \ \alpha]$, we solve for the value function and the optimal policy function. The goal is to identify the parameters that match the actual data moments, denoted as M_d, with simulated moments, denoted as $m_s(\Theta)$. The parameter estimates therefore are chosen to minimize the weighted distance between actual moments and simulated moments:

$$\hat{\Theta} = arg \min_{\Theta} [M_d - \frac{1}{S} \sum_{s=1}^{S} m_s(\Theta)] W [M_d - \frac{1}{S} \sum_{s=1}^{S} m_s(\Theta)],$$

where W is the optimal weighting matrix which is given by the inverse of the variance-covariance matrix of M_d. We create $S = 6$ artificial panels containing 1000 firms (paths) with 40 time periods. For each path, the log state variable a is restricted to the discretized set of values. We simulate 60 periods for each firm and drop the first 20 periods to allow the firms to move away from a possibly suboptimal starting point (see Hennessy & Whited 2005). At the end of each panel, we run the baseline regression of investment on q and cash flow. And then we take the average of the cash flow coefficients and q coefficients over the S panels and form our simulated moments.

The estimation output for each subsample period is reported in Table 2.5. Table 2.5 shows that the capital adjustment cost parameter estimated with simulated method of moments display an increasing time trend, which is consistent with our previous findings. It further proves the the increasing pattern of capital adjustment costs is robust despite different estimation methodology.

Table 2.5: Parameter estimation with simulated method of moments in each subsample period

β_1 is q sensitivity of investment from baseline regression and β_2 is cash flow sensitivity of investment. The second and third columns display β_1 and β_2 computed from actual data in each subsample period. The third and fourth column display β_1 and β_2 computed from data simulated with the relevant model parameters. The last two columns report the estimated model parameters γ and α that minimize the weighted distance between the actual moments and the simulated moments.

	Actual Moments		Simulated Moments		Parameter Estimates	
Period	β_1	β_2	β_1	β_2	γ	α
1977-1981	0.0231	0.2830	0.0264	0.2736	0.4866	0.3909
1982-1986	0.0228	0.1351	0.0214	0.1380	0.7860	0.3938
1987-1991	0.0164	0.0650	0.0144	0.0770	1.1009	0.3816
1992-1996	0.0117	0.0528	0.0086	0.0489	1.4680	0.6045
1997-2001	0.0077	0.0266	0.0076	0.0253	1.2753	0.5196
2002-2006	0.0060	0.0055	0.0048	0.0090	6.9163	0.5365
2007-2011	0.0069	-0.0015	0.0044	0.0017	4.4352	0.6955
2012-2016	0.0046	0.0048	0.0027	0.0077	3.2007	0.5941

2.4.3.2 Time-varying adjustment cost parameter

In this section, we introduce time variations in the model and reexamine the firms' value-maximization problem under time-varying adjustment cost parameter. In this situation, managers are fully rational and perceive adjustment costs in the next period based on what they have observed now. We allow γ to vary according to a finite-state Markov-chain process. This results in three state variables for the firms' optimization problem: profitability shock A, capital stock K and adjustment cost parameter γ. We rewrite the firm's value as

$$V(A, K, \gamma) = \max_{I}[(\Pi(A, K) - I - G(I, K, \gamma) - H(X, K)) + \theta E_{\{A'|A;\gamma'|\gamma\}}V(A', K', \gamma')].$$

We assume that γ follows a AR(1) process in logs

$$log(\gamma') = \mu_g + \rho_g log(\gamma) + \sigma_g \epsilon_g',$$

where $\epsilon_g \sim N(0, 1)$ represents the aggregate shock to investment frictions that defines the general state of the economy. This specific process captures the nature of mean reversion, which is important to obtain the stationarity for capital adjustment costs in the long run. $1 - \rho_g$ defines the speed of mean reversion and $0 < \rho_g < 1$ to ensure that capital adjustment cost does not explode. μ_g is the constant term where $\frac{\mu_g}{1-\rho_g}$ defines the mean level that $log(\gamma)$ tend to revert to. σ_g is the process volatility. This initial level of γ (denoted as γ_0) matters as it determines the trend of the process. The mean level of γ is computed as $e^{\frac{\mu_g}{(1-\rho_g)} + 0.5\frac{\sigma_g^2}{(1-\rho_g^2)}}$. If the initial level is lower (higher) than the mean level, then γ tends to rise (fall) over time. The parameters picked to reproduce the time-series pattern of investment-cash flow sensitivity estimated in the actual data are hence $[\gamma_0 \ \rho_g \ \mu_g \ \sigma_g \ \alpha]$ (see Section 2.4.3 for the selection of α). For the parameter set chosen, we solve for the model and simulate one time-series of γ for all firms and one time-series of A for each of the firm. Our simulation consists of 10 panels, each of which includes 1000 firms and 80 model periods. We start the simulation with the randomly-drawn firm-specific profit shocks (A) and the corresponding no-adjustment-cost steady-state capital (K). We allow γ to be fixed at γ_0 for the first 20 periods before we remove them to eliminate the impact of the initial condition. We intend to match the simulated cash flow coefficients (β_2) estimated per model period to those estimated yearly from the actual data. This is equivalent to matching 40 moments, each corresponding to the cash flow coefficient in one year.

Estimation is carried out to match the time-series variation of β_2. The parameter set that deliver the pattern closest to that in the actual data is outlined in Table 2.6. The left graph in Figure 2.1 plots the process of adjustment cost parameter simulated with the parameter set. It starts from the value of around 1.7 and increases up to 3.3. The corresponding investment-cash flow sensitivity regressed with the model-simulated data is plotted in solid line on the right graph. The deviations of simulated β_2 from actual β_2 are generally small except for a few years at the beginning. Again, the rising trend of γ is observed, which accounts for the decreasing pattern of β_2

Table 2.6: Parameter estimation results

The table represents the output for parameter estimates governing the stochastic process of adjustment cost parameter. If the initial level, γ_0, is lower (higher) than the long-run mean level, then γ tends to rise (fall) over time.

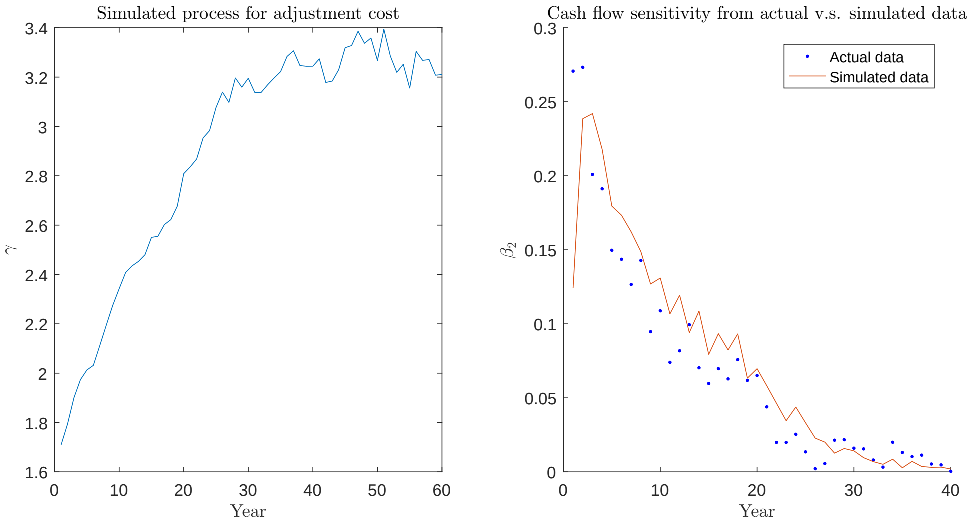
Parameter		
Mean reversion coefficient	ρ_g	0.9319
Initial γ	γ_0	1.7171
Mean of log(γ)	μ_g	0.0816
Volatility of log(γ)	σ_g	0.0401
Returns to scale	α	0.7020
The long-run mean	$e^{\frac{\mu_g}{(1-\rho_g)}+0.5\frac{\sigma_g^2}{(1-\rho_g^2)}}$	3.3346

2.4.4 Evidence based on the industry-level data

2.4.4.1 Technological changes and capital adjustment costs

The innovations of technology have evolved significantly over the past 30 years. In 1977, Ken Olsen, who co-founded the Digital Equipment Corporation, said, “There is

Figure 2.1: Simulated process of γ and estimated β_2



The left graph plots the evolution of adjustment cost parameter simulated with the parameter set in Table 2.6. The solid line in the right graph plots the corresponding investment-cash flow sensitivity regressed with the model-simulated data and the dots display the cash flow coefficients regressed with actual data.

no reason for any individual to have a computer in his home". Nowadays, almost every individual owns at least one personal computer at home. According to a business review from *The Economist*, technological breakthroughs can be disruptive as "they completely overturn existing products and markets" (Economist n.d.). An industry report from PwC has referred to 3D printing as a disruptive technology and the costs that ensue are the shortage of talent, the need to establish digital platforms and to restructure the current operations and, the demand for a new system to permit integration of activities (PwC 2016). Based on a business report from McKinsey (McKinsey & Company 2017), the manufacturing organizations have entered a new era with the advances in automation, robotics and artificial intelligence, which necessitate the adaption, integration and development of the technology into business solutions and the time costs for labor to retrain into the high-skill positions. Current economic literature, based on industry-level evidence, provides some insights into the evolution of adjustment costs relating to the technological development. Technological progress may lead to large capital adjustment costs. For example, Hornstein & Krusell (1996) and Greenwood & Yorukoglu (1997) suggest that technological improvement can cause productivity slowdown as the adoption of new capital introduces high costs of learning. (Even though there is ongoing debate about the relationship between technology and productivity growth because the measurement of productivity is not definitive, their arguments do not provide inferences about the effect of technology on capital adjustment costs.) Kiley (2001) presents evidence of large costs associated with training and maintaining information technologies. Bessen (2002) ascribes the possible cause of the rise in adjustment costs to the rise in information technology spending, e.g., customization of softwares. Groth (2008) estimates that it is more costly to install capital in ICT-intensive (ICT standing for information-communication technology) industries (see also Bessen (2002) for high adjustment costs estimated for high-tech industries). Uchida, Takeda & Shirai (2012) can only identify costs of capital adjustment for the sectors that have undergone a technological change in automobile electronics. Although Meghir, Ryan & Van Reenen (1996) challenge the technologically sluggish arguments and assert that innovative firms face lower adjustment costs as innovation brings them more flexibility (see also Smolny (1998) for relevant statement), their approach differs from from us as they draw inference from the evidence in the labor market.

As documented in Gordon (1990), the rate of technology growth, as implied by the decline in the relative price of investment goods, has been remarkable (Oliner & Sichel 2000, Jorgenson & Stiroh 2000). In Figure 2.2, we illustrate the trend in technological innovations. The figure shows that the acquisition of equipment and computer software in US has increased over time, although experiencing a decline due to the impact of the financial crisis. With high-tech equipment embedded into the work, the lack of technical skills to install and operate the equipment seems to be a significant problem. Firms, in order to prevent the loss of committed employees, need to provide proper training to help their workforce adapt to the new machines and tools. The workers, while devoting extra hours to acquiring new skills, have to forgo some output, which constitutes a substantial part of capital adjustment costs . We refer to the education and training participation rate in European countries to draw inference about the participation of training program in the US. The data is extracted from Eurostat (the earliest data for training participation rate is 1992) and we plot the average of participation rate in education and training by employed persons across Austria, Belgium, Denmark, Finland, France, Portugal, Germany, Greece, Italy, Ireland, Luxembourg, Netherlands, Norway, Spain, Sweden, Switzerland and United Kingdom from 1992 to 2017 in Figure 2.2(b). The percentage of employees taking part in eduction and training climb to around 14% in the recent years from 6% in 1990. The rise in the participation rate in education and training programs indicates higher training fees or learning costs accompanying the adoption of new technology, which provides a basis for the increasing capital adjustment costs.

Figure 2.2: The acquisition of high-tech equipment and participation of training by workers

(a) ICT acquisition (b) Participation in education and training

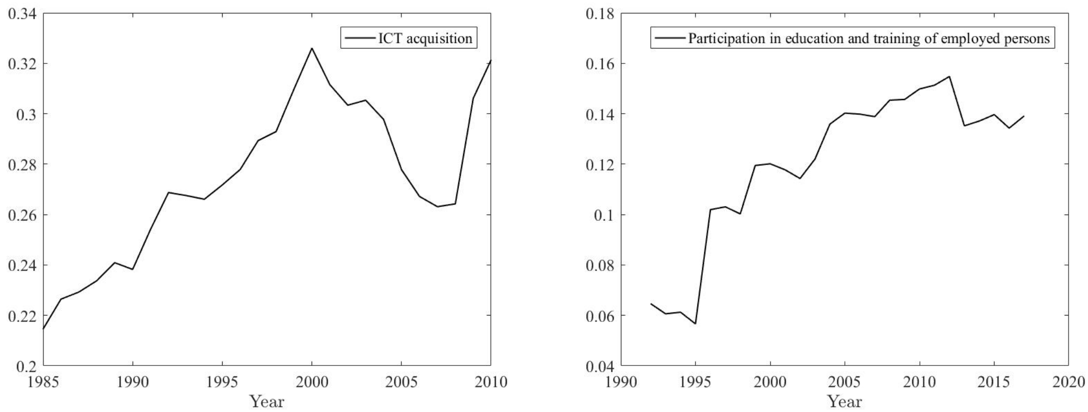


Figure 2.2(a) plots the acquisition of equipment and computer software that is used in production for more than one year from 1985 to 2011 for US. Figure 2.2(b) plots the average percentage of employed persons in European countries that have taken part in education and training from 1992 to 2017.

2.4.4.2 Estimation with industry-level data

Following the literature that relates adjustment costs to productivity growth, we adopt the approach of Bessen (2002) and estimate the trend of adjustment costs with 4-digit SIC code industry-level data drawn from "NBER-CES Manufacturing Industry Database" covering periods between 1977 and 2011. The adjustment cost is defined as the deviation of the actual output from the potential output. For each industry j, we have $Y_t = Y_t^*(1-G_t)$ where the potential output is $Y_t^* = A_t K_t^{\alpha_{K,t}} M_t^{\alpha_{M,t}} L_t^{\alpha_{L,t}}$ (A_t denotes productivity shock, M_t defines material input, L_t is labor input, $\alpha_{K,t}$ ($\alpha_{M,t}$, $\alpha_{L,t}$) is capital (material, labor) share) and actual output is Y_t. $G_t = \gamma \frac{I_{t-1}}{K_{t-1}}$ is adjustment cost per unit of potential output which is linearly related to the lagged investment-capital ratio. $1 - G_t$ is analogous to the speed of adjustment (SOA) in the partial adjustment model of Lintner (1956) (see also SOA under the framework of capital structure in Flannery & Rangan (2006)). The SOA in this context is the rate at which firm adjusts the output to its target (potential) level. Low $1 - G_t$ indicates low speed of adjustment or high level of adjustment costs. For the industry j at time t, we take logs, take difference and rearrange $Y_{jt} = Y_{jt}^*(1 - G_{jt})$ and then we yield ($\widehat{\cdot}$ denotes log change)

$$\widehat{Z_{jt}} \equiv \widehat{Y_{jt}} - \alpha_{K,jt}\widehat{K_{jt}} - \alpha_{M,jt}\widehat{M_{jt}} - \alpha_{L,jt}\widehat{L_{jt}} = \widehat{A_{jt}} - \gamma \Delta \frac{I_{jt-1}}{K_{jt-1}},$$

and γ can be estimated by regressing $\widehat{Z_{jt}}$ on $\Delta \frac{I_{jt-1}}{K_{jt-1}}$. In order to gauge the time pattern of adjustment costs, we include the period trend variable T which is 1 in 1977-1981, 2 in 1982-1987 and so forth. Table 2.7 presents the regression output for the pattern of adjustment cost. The coefficient on $T \times \Delta \frac{I_{jt-1}}{K_{jt-1}}$ shows that the adjustment cost parameter has increased by 0.05 in each period when year dummies are not included and increased by 0.015, although it is statistically insignificant, when time fixed effect is accounted for. Even though the increasing trend of adjustment costs is attenuated when aggregate shocks are controlled for, the coefficient on $T \times \Delta \frac{I_{jt-1}}{K_{jt-1}}$ produces the right sign and demonstrates an increase in adjustment costs. To sum up, combining the time-series evolution of adjustment cost parameter γ with its negative impact on I-CF sensitivity, we accept our second prediction and argue that the declining trend of I-CF sensitivity can be explained by the rising adjustment cost parameter.

Table 2.7: Adjustment to the potential output level

The OLS regression output are based on data from "NBER-CES Manufacturing Industry Database" covering periods between 1977 and 2011. The dependent variable is productivity residual growth $\widehat{Z_{jt}}$ as described in Bessen (2002). The explanatory variables are lagged change of investment-capital ratio $\Delta\frac{I_{jt-1}}{K_{jt-1}}$, interaction term between period trend variable T and lagged change of investment-capital ratio. Period trend variable is defined as 1 in 1977-1981 and 2 in 1982-1986 and so forth. Standard errors are clustered in industry level and reported in parenthesis. Adjusted R square is also reported. ***, **, *indicate significance at the 1%, 5% and 10% levels.

Variables	Dependent variable is $\widehat{Z_{jt}}$		
$\Delta\frac{I_{jt-1}}{K_{jt-1}}$	-0.094	-0.099	-0.196**
	(0.085)	(0.098)	(0.087)
$T \times \Delta\frac{I_{jt-1}}{K_{jt-1}}$	-0.053**	-0.052***	-0.015
	(0.019)	(0.021)	(0.019)
Industry dummies		Yes	Yes
Year dummies			Yes
R_a^2	0.015	0.014	0.127

The following regression output is based on stochastic frontier model.. The data variables is as described above ***, **, *indicate significance at the 1%, 5% and 10% levels.

Variables	Dependent variable is $\widehat{Z_{jt}}$		
$\Delta\frac{I_{jt-1}}{K_{jt-1}}$	-0.092	-0.089	-0.186***
	(0.058)	(0.058)	(0.056)
$T \times \Delta\frac{I_{jt-1}}{K_{jt-1}}$	-0.053***	-0.054***	-0.017
	(0.013)	(0.013)	(0.012)
Industry dummies		Yes	Yes
Year dummies			Yes

2.5 Robustness analysis

2.5.1 Cross-country evidence based on Moshirian et al. (2017)

Moshirian et al. (2017) examine the difference in I-CF sensitivities between the firms from the developed economies and those from the developing countries. They demonstrate that the decrease in I-CF sensitivities is significant for developed countries and moderate for developing economies. They introduce the role of asset tangibility. They argue that the decline in the importance or the productivity of tangible asset and also the decline in the income predicability leads to the decreasing pattern of I-CF sensitivities in the "new economy". [11]

However, in this paper, we provide an alternative explanations for the observed difference in I-CF sensitivities between developed economies and developing economies. Firms in the developed countries are faster in adopting the technology-intensive physical capital and hence should experience a more significant increase in the capital adjustment costs over time. Therefore, their I-CF sensitivities decline substantially even though the productivity of physical capital is held constant or fully controlled for. Firms in the developing economies, however, face a moderate growth in their technologies and capital adjustment costs. Therefore, their I-CF sensitivities should decline at a lower pace or face no decline until recently.

2.5.2 Cross-industry regression results

As a robustness check, we divide the manufacturing firms based on the definition in Chen & Chen (2012) into three industry groups: durables, nondurables, and high-tech

[11] As I-CF sensitivities refers to the estimated coefficient on cash flow after controlling for Tobin's q, which is the proxy for the marginal productivity of physical capital, the argument is aligned with the measurement error theory of q (Erickson & Whited 2000). Cash flow contains the information regarding the productivity of tangible asset as Tobin's q does a poor job in capturing it. And the low I-CF sensitivity in the recent periods is the result of the low measurement error in q, which makes cash flow become a less predictable variable for investment.

industries. Within each industry group, we run the baseline regression from 1977-1981 to 2012-2016. As high-tech firms possess higher proportion of technology-intensive capital as compared to non-hightech groups, we expect that the high-tech groups undergo higher increase in capital adjustment costs over time and thereby more decline in I-CF sensitivity. Table 2.8 shows a decreasing pattern of I-CF sensitivity regardless of the industry group the firms belong to. It also shows that I-CF sensitivity for the high-tech industries has shrunk more severely in 2000s than the other industry groups. It starts to disappear in 2002-2006 and remains comparatively low in recent decades compared with other industry groups. In order to provide a more concrete comparison of the declining trend of I-CF sensitivity across industries, we estimate β_2 by year and regress the natural log of β_2 on year trend variable which is equal to 1 for 1977, 2 for 1978 and so forth (the corresponding regression estimates is denoted as η). Table 2.9 reveals that I-CF sensitivity drops by 9.3% (5.4%) for durables (nondurables) every year while β_2 decreases by 11.5% every year for high-tech groups. To get a clearer picture, we also report the t statistics and the corresponding p values for the null hypothesis that the declining trend of β_2 is the same between high-tech and durables (nondurables). Both comparisons (high-tech v.s. durable and high-tech v.s. nondurable) show that the declining trend of β_2 (captured by η) is significantly more prominent for high-tech groups than that for durable groups and nondurable groups.

Table 2.8: Estimation across industry groups

The table reports the estimation results for the industry group in each of the panel. The second and third column in the table report q coefficient and cash flow coefficient estimated from baseline linear regression. The fifth and sixth column report γ and b estimated based on the q equation. The results are displayed for each industry group: durables, nondurables and high-tech industries. p value for the null hypothesis that the coefficients are the same between the first period and the last period is reported below. ***, **, *indicate significance at the 1%, 5% and 10% levels.

	Durables:		Nondurables:		High-tech:	
Period	β_1	β_2	β_1	β_2	β_1	β_2
1977-1981	0.017***	0.287***	0.021***	0.287***	0.034***	0.289***
1982-1986	0.023***	0.139***	0.018***	0.177***	0.024***	0.117***
1987-1991	0.013***	0.066***	0.017***	0.093***	0.017***	0.059***
1992-1996	0.011***	0.066***	0.009***	0.046***	0.012***	0.05***
1997-2001	0.011***	0.036***	0.013***	0.044*	0.007***	0.018*
2002-2006	0.009***	0.016	0.006***	0.017	0.006***	-0.001
2007-2011	0.009***	-0.004	0.009***	0.004	0.006***	-0.004
2012-2016	0.005***	0.012	0.003	0.006	0.005***	0.002
p value	0.076	0.000	0.010	0.000	0.000	0.000

Table 2.9: Comparisons of the trend in β_2 across industry groups

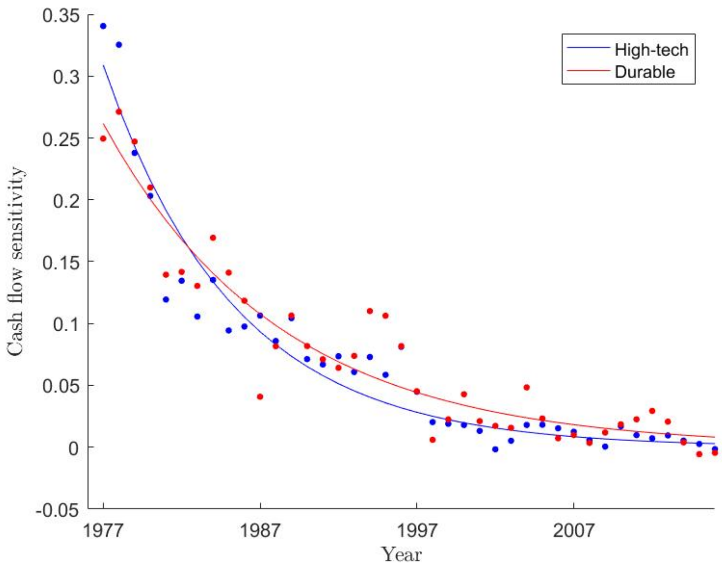
The table shows estimates of the declining trend for β_2, denoted as η, across each industry group, namely durables, nondurables and high-tech. η is estimated by regressing the natural log of β_2 on year trend variable, which is equal to 1 for 1977, 2 for 1978 and so forth. Robust standard errors are shown in parenthesis. t statistics and corresponding p values for the null hypothesis that the declining trend is the same between high-tech and durables (nondurables) are reported. ***, **, *indicate significance at the 1%, 5% and 10% levels.

	Durable	Nondurable	High-tech
η	-0.093***	-0.054***	-0.115***
	(0.009)	(0.009)	(0.006)
H0: η(High-tech)=η(Durable)			
t stats:	-1.739	p value:	0.086
H0: η(High-tech)=η(Nondurable)			
t stats:	-5.391	p value:	0.000

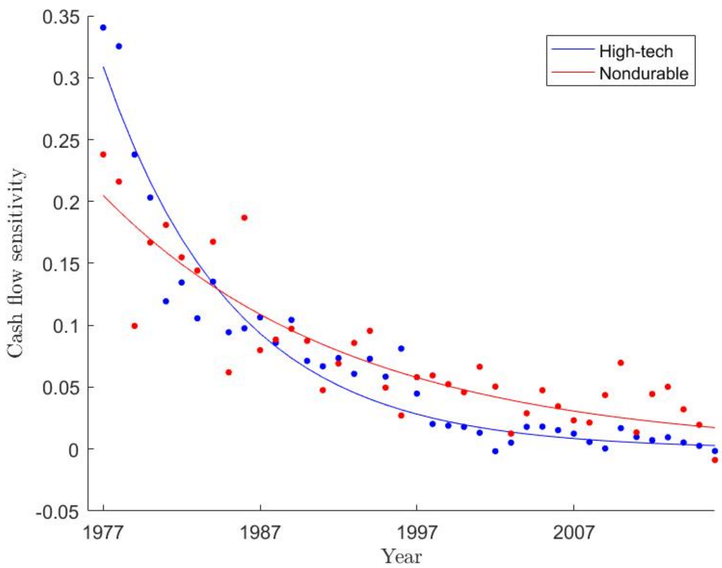
The comparison of declining trend is further illustrated in Figure 2.3 with scatter plots and exponential curve fitting. The observation that high-tech firms have experienced more decline in their I-CF sensitivities is consistent with the fact they have incurred higher costs in capital adjustment over time. In all, based on the increasing adoption of information technology and communications equipment and computer software (as

Figure 2.3: Investment-cash flow sensitivity across industries by year (fitted with an exponential curve)

High-tech v.s. Durable goods



High-tech v.s. Nondurable goods



Note: The top graph shows the scatter plots of investment-cash flow sensitivities estimated for high-tech (blue) v.s. durable (red) industry fitted with an exponential curve from 1977 to 2016. The bottom graph shows the scatter plots of investment-cash flow sensitivities estimated for high-tech (blue) v.s. nondurable (red) industry fitted with an exponential curve from 1977 to 2016.

shown in Figure 2.2(a)), the low I-CF sensitivity we observe in the late years aligns with the fact the firms has shifted towards high-tech machines and equipment, which incurred higher costs in installation and adjustment.

2.6 Conclusions

We study the I-CF sensitivity phenomenon in a time series context to address the puzzling question of the reason behind the gradual decline of this sensitivity over time. We focus our attention on two key factors inspired by a neoclassical investment framework with costly external financing: financial frictions and capital adjustment costs. To evaluate whether those factors contribute to the declining pattern of I-CF sensitivity, we use a broad set of tests ranging from a nonlinear estimation of the first order condition, a GMM estimation of Euler equation to a structural estimation of the parameters.

We demonstrate that while I-CF sensitivity is a specific function of both financial constraints and capital adjustment costs, it is mainly the evolution over time of the latter that is capable of explaining the declining I-CF pattern. As firms need to allocate their internal funds to the finance of both investment and capital adjustment costs, higher adjustment costs will lead to a lower sensitivity of investment to cash flow. We show that capital adjustment costs have demonstrated an increasing time trend, which explains why I-CF sensitivity has declined over time.

Consistent with the extant literature, we do not find evidence of the sufficient changes in the magnitude of financing frictions that would be consistent with the observed pattern. More generally, we demonstrate that the I-CF sensitivity reflects not only financing but also real frictions. This observation has implications for the design of empirical tests of financing constraints using the I-CF framework, which need to take into account effects of technological change leading to variations in the cost of capital stock adjustment.

2.A. Derivation of the profit function

To derive the profit function of the firm, consider first its Cobb-Douglas production function

$$F(\tilde{A}, K, L, M) = \tilde{A}K^{\alpha_K}M^{\alpha_M}L^{\alpha_L},$$

where $\tilde{A}$ indexes technology shock, K is physical capital input, M is material input and L is labor input. Denote p as output price and assume price is taken as given in a competitive market. p_M is price for material, W is wage (price for labor input). Assume labor and material input are short-run flexible factors, we had the profit (operating cash flow) function as

$$\Pi = \max_{L,M} p\tilde{A}K^{\alpha_K}M^{\alpha_M}L^{\alpha_L} - WL - p_M M.$$

Take derivative with respect to L and M, we have

$$WL = p\alpha_L\tilde{A}K^{\alpha_K}M^{\alpha_M}L^{\alpha_L}, \tag{2.A.1}$$

$$p_M M = p\alpha_M\tilde{A}K^{\alpha_K}M^{\alpha_M}L^{\alpha_L}. \tag{2.A.2}$$

Substitute the optimal L and M back into profit function, we have

$$\Pi = AK^{\alpha},$$

where $A = (1 - \alpha_M - \alpha_L)\tilde{A}^{\frac{1}{1-\alpha_M-\alpha_L}} p^{\frac{1}{1-\alpha_M-\alpha_L}} \alpha_L^{\frac{\alpha_L}{1-\alpha_M-\alpha_L}} \alpha_M^{\frac{\alpha_M}{1-\alpha_M-\alpha_L}} W^{\frac{\alpha_L}{\alpha_M+\alpha_L-1}} p_M^{\frac{\alpha_M}{\alpha_M+\alpha_L-1}}$ and $\alpha = \frac{\alpha_K}{1-\alpha_M-\alpha_L}$.

2.B. Model in a perfect capital market

In this appendix, we derive the optimality condition assuming external financing is frictionless. There is a perfect capital market and hence any shortage of funds to finance the investment can be raised from external market costlessly. The Bellman equation characterizing the firm's dynamic optimization problem is

$$V(A_t, K_t) = \max_{I_t} \left[(\Pi(A_t, K_t) - I_t - G(I_t, K_t)) + \theta E_{A_{t+1}|A_t} V(A_{t+1}, K_{t+1}) \right], \quad (2.B.3)$$

where θ denotes the discount factor and the marginal Tobin's q is $\beta E_{A_{t+1}|A_t} V_K(A_{t+1}, K_{t+1})$. The first-order condition with respect to I_t yields

$$q_t = 1 + \gamma \frac{I_t}{K_t}. \quad (2.B.4)$$

We have therefore arrived at the q equation which equates the marginal return of investment with its marginal cost. Upon rearranging (2.B.4), we obtain

$$\frac{I_t}{K_t} = -\frac{1}{\gamma} + \frac{1}{\gamma} q_t.$$

Therefore, under perfect capital market, the marginal q is a sufficient statistic for corporate investment.

Extant empirical work tends to include cash flow as an additional variable when running the regression of investment. The following baseline regression is typically used (cf. Fazzari et al.):

$$\frac{I_t}{K_t} = \beta_0 + \beta_1 q_t + \beta_2 \frac{CF_t}{K_t} + \varepsilon_t. \quad (2.B.5)$$

It is worth noting that cash flow variable ($\frac{CF}{K}$) is added to the regression in an ad hoc way and marginal q is frequently proxied by average q, defined as the market value of capital over the book value of capital. If the assumptions of linear homogeneity and perfect competition stated in Hayashi (1982) hold, Tobin's average q will be a perfect proxy for marginal q. As marginal q is the sole statistic for investment in a perfect capital market, β_2 should therefore be zero.

2.C. Derivation of I-CF and I-q sensitivities

Calculation of the partial derivative of investment with respect to cash flow is performed as follows. Eqn (2.3.1) has that

$$1 + \gamma \left(\frac{I}{K}\right)^{\psi-1} + b\Phi \left(\frac{I}{K} - \frac{\Pi}{K}\right) = q. \tag{2.C.1}$$

Differentiating (2.C.1) with respect to $\frac{\Pi}{K}$ on both sides

$$\gamma(\psi - 1) \left(\frac{I}{K}\right)^{\psi-2} \frac{\partial I/K}{\partial \Pi/K} + b\Phi \frac{\partial I/K}{\partial \Pi/K} - b\Phi = 0.$$

After rearranging, one obtains

$$\frac{\partial I/K}{\partial \Pi/K} = \frac{b\Phi}{\gamma(\psi - 1)(\frac{I}{K})^{\psi-2} + b\Phi}. \tag{2.C.2}$$

Similarly, we differentiate (2.C.2) with respect to q on both sides

$$\gamma(\psi - 1) \left(\frac{I}{K}\right)^{\psi-2} \frac{\partial I/K}{\partial q} + b\Phi \frac{\partial I/K}{\partial q} = 1.$$

This yields

$$\frac{\partial I/K}{\partial q} = \frac{1}{\gamma(\psi - 1)(\frac{I}{K})^{\psi-2} + b\Phi}. \tag{2.C.3}$$

2.D. Euler investment equation: An empirical counterpart

The estimation equation for the Euler investment equation is derived as follows. The firm aims to maximize expected discounted value of the stream of future net profit where

$$V(A_t, K_t) = \max_{\{K_{\tau+1}, I_\tau\}_{\tau=t}^{\infty}} E_t \sum_{\tau=t} (\frac{1}{1+r})^{\tau-t} (\Pi(A_\tau, K_\tau) - I_\tau - G(I_\tau, K_\tau) - H(X_\tau, K_\tau)), \tag{2.D.1}$$

subject to $I_t = K_{t+1} - (1-\delta)K_t$. The functions are as previously defined. The Lagrange function with lagrange multiplier q_τ is

$$\mathcal{L} = \max_{\{K_{\tau+1}, I_\tau\}_{\tau=t}^{\infty}} E_t \sum_{\tau=t} (\frac{1}{1+r})^{\tau-t} (\Pi(A_\tau, K_\tau) - I_\tau - G(I_\tau, K_\tau) - H(X_\tau, K_\tau) + q_\tau (I_\tau + (1-\delta)K_\tau - K_{\tau+1})),$$

where q_t is the shadow price of capital. First order condition with respect to I_t, K_{t+1} have

$$\frac{\partial \mathcal{L}}{\partial I_t} = 0 \Rightarrow q_t = 1 + \frac{\partial G(I_t, K_t)}{\partial I_t} + \frac{\partial H(X_t, K_t)}{\partial I_t}, \tag{2.D.2}$$

$$\frac{\partial \mathcal{L}}{\partial K_{t+1}} = 0 \Rightarrow q_t = \frac{1}{1+r} E_t[(1-\delta) q_{t+1} + \frac{\partial \Pi(A_{t+1}, K_{t+1})}{\partial K_{t+1}} - \frac{\partial G(I_{t+1}, K_{t+1})}{\partial K_{t+1}} - \frac{\partial H(X_{t+1}, K_{t+1})}{\partial K_{t+1}}]. \tag{2.D.3}$$

With iterative substitution of (2.D.3) and transversally condition that $\lim_{T\to\infty} \frac{q_{t+T}}{(1+r)^{t+T}} = 0$, we obtain

$$q_t = E_t \sum_{\tau=t+1}^{\infty} \frac{(1-\delta)^{\tau-t-1}}{(1+r)^{\tau-t}} [\frac{\partial \Pi(A_\tau, K_\tau)}{\partial K_\tau} - \frac{\partial G(I_\tau, K_\tau)}{\partial K_\tau} - \frac{\partial H(X_\tau, K_\tau)}{\partial K_\tau}]. \tag{2.D.4}$$

Substitute (2.D.2) into (2.D.3), we have

$$\begin{aligned} & 1 + \frac{\partial G(I_t, K_t)}{\partial I_t} + \frac{\partial H(X_t, K_t)}{\partial I_t} = \\ & \frac{1}{1+r} E_t[(1-\delta)(1 + \frac{\partial G(I_{t+1}, K_{t+1})}{\partial I_{t+1}} + \\ & \frac{\partial H(X_{t+1}, K_{t+1})}{\partial I_{t+1}}) + \frac{\partial \Pi(A_{t+1}, K_{t+1})}{\partial K_{t+1}} - \frac{\partial G(I_{t+1}, K_{t+1})}{\partial K_{t+1}} - \frac{\partial H(X_{t+1}, K_{t+1})}{\partial K_{t+1}}]. \end{aligned} \tag{2.D.5}$$

In writing the empirical equation, we assume that production function displays constant returns to scale in the perfect competitive market such that $\frac{\partial \Pi(A_t, K_t)}{\partial K_t} = \frac{\Pi_t}{K_t}$. Assuming quadratic form for adjustment cost function, we have $\frac{\partial G(I_t, K_t)}{\partial I_t} = \gamma \frac{I}{K}_t$ and $\frac{\partial G(I_t, K_t)}{\partial K_t} =$

$-\frac{1}{2}\gamma\left(\frac{I}{K}_t\right)^2$. Also $\frac{\partial H(X_t,K_t)}{\partial I_t} = b\phi(\frac{I}{K}_t - \frac{\Pi}{K}_t)$ and $\frac{\partial H(X_t,K_t)}{\partial K_t} = -\frac{1}{2}b\phi\left(\frac{I}{K}_t - \frac{\Pi}{K}_t\right)\left(\frac{I}{K}_t + \frac{\Pi}{K}_t\right)$. Adding an expectation error ϵ_{t+1} where $E_t(\epsilon_{t+1}) = 0$ to remove the expectation operator, we arrive at the estimation equation for the Euler equation:

$$\begin{aligned}
&\frac{1}{1+r}\Big[(1-\delta)\left(1+\gamma\left(\frac{I}{K}_{t+1}\right)+b\phi\left(\frac{I}{K}_{t+1}-\frac{\Pi}{K}_{t+1}\right)\right)+\\
&\frac{\Pi}{K}_{t+1}+\frac{1}{2}\gamma\left(\frac{I}{K}_{t+1}\right)^2+\frac{1}{2}b\phi\left(\frac{I}{K}_{t+1}-\frac{\Pi}{K}_{t+1}\right)\left(\frac{I}{K}_{t+1}+\frac{\Pi}{K}_{t+1}\right)\Big]+\epsilon_{t+1}\\
&=1+\gamma\left(\frac{I}{K}_t\right)+b\phi\left(\frac{I}{K}_t-\frac{\Pi}{K}_t\right). \qquad (2.D.6)
\end{aligned}$$

2.E. I-CF sensitivity with nonconvex and convex capital adjustment costs

As in Whited (2006), we consider the fact that investment incurs fixed (nonconvex) costs which are proportional to the capital stock, denoted as fK. The fixed costs only occur during periods of active investment. As stated in Cooper & Haltiwanger (2006), the fixed costs reflect the needs for restructuring and retraining of the activities and therefore they only take place when new investment is made. The firm value $V(A_t, K_t)$ is therefore written as:

$$V(A_t, K_t) = \max\{V^a(A_t, K_t), V^n(A_t, K_t)\}, \tag{2.E.1}$$

in which $V^n(A_t, K_t)$ ($V^a(A_t, K_t)$) reflects the firm value when no (active) investment is made. The corresponding Bellman equations are:

$$V^a(A_t, K_t) = \max_{I_t}[(\Pi(A_t, K_t) - I_t - fK - G(I_t, K_t) - H(X_t, K_t)) + \theta E_{A_{t+1}|A_t} V(A_{t+1}, K_{t+1})],$$

and

$$V^n(A_t, K_t) = [\Pi(A_t, K_t) + \theta E_{A_{t+1}|A_t} V(A_{t+1}, (1-\delta)K_t)].$$

The parameters are as defined before. The first order condition when active investment is made is:

$$1 + \gamma\left(\frac{I_t}{K_t}\right)^{\psi-1} + b\Phi\left(\frac{I_t}{K_t} - \frac{\Pi_t}{K_t}\right) = q_t, \tag{2.E.2}$$

where $q_t = \theta E_{A_{t+1}|A_t} V_K^a(A_{t+1}, K_{t+1})$. Consider $\mathbf{1}(I > 0)$ as the indictor that active investment is made, then I-CF sensitivity can be derived as:

$$\frac{\partial I/K}{\partial \Pi/K} = \frac{b\Phi}{\gamma(\psi-1)(\frac{I}{K})^{\psi-2} + b\Phi}\mathbf{1}(I > 0). \tag{2.E.3}$$

It can be seen that a fixed cost of capital adjustment influences I-CF sensitivity by affecting the probability of making active investment. High fixed cost f decreases the probability of active investment and the mean value of $\mathbf{1}(I > 0)$ and leads to a *lower*

I-CF sensitivity. Nonetheless, in the firm-level data, we can rarely observe the inactive investment (thereby $\mathbf{1}(I > 0)$ is always 1), which make it difficult to identify the effect of a fixed cost on the cash flow sensitivity of investment.

2.F. Estimations without winsorization

This Appendix provide the baseline regression results and nonlinear estimations results of q equation for data without winsorization. The estimates of I-CF sensitivity, namely β_2, also steadily decline over time. The rising trend of capital adjustment cost parameters is still prominent for the data without winsorization.

Table 2.10: Baseline regression and estimation of q equation without winsorization

This table on the left side reports estimation results from baseline linear regression model $\frac{I_{it}}{K_{it-1}} = \beta_0 + \beta_1 Q_{it-1} + \beta_2 \frac{CF_{it}}{K_{it-1}} + \eta_i + \eta_t + \varepsilon_{it}$ in each five-year subsample period. $\frac{I_{it}}{K_{it-1}}$, $\frac{CF_{it}}{K_{it-1}}$, Q_{it-1}, η_i, η_t are all as previously described. The table on the right side reports the estimates for γ, ψ and b based on Eqn (2.5). Adjusted R square R_a^2 are reported. ***, **, *indicate significance at the 1%, 5% and 10% levels.

Period	β_1	β_2	R_a^2	γ	ψ	b	R_a^2
1977-1981	0.019***	0.246***	0.568	2.620***	1.773***	0.910	0.164
	(0.007)	(0.039)		(0.295)	(0.157)	(0.784)	
1982-1986	0.020***	0.091***	0.515	6.374***	1.724***	0.101	0.181
	(0.005)	(0.021)		(0.178)	(0.052)	(0.186)	
1987-1991	0.013***	0.054***	0.538	6.778***	1.935***	1.067***	0.140
	0.003	0.013		(0.363)	(0.103)	(0.241)	
1992-1996	0.006***	0.029***	0.607	15.618***	1.802***	2.678***	0.090
	0.001	0.012		(1.876)	(0.159)	(0.707)	
1997-2001	0.005***	0.010	0.540	21.472***	1.729***	1.535***	0.155
	0.001	0.006		(1.228)	(0.078)	(0.345)	
2002-2006	0.004***	0.001	0.575	35.495***	1.841***	2.726***	0.251
	0.001	0.005		(0.883)	(0.048)	(0.536)	
2007-2011	0.004***	-0.012*	0.466	28.633***	1.666***	3.280***	0.206
	0.001	0.007		(1.479)	(0.098)	(1.265)	
2012-2016	0.004***	-0.001	0.607	38.895***	1.900***	3.586***	0.389
	0.001	0.006		(1.849)	(0.103)	(0.132)	

Chapter 3

The prolonged effect of collateral shocks in the context of capital and labor dynamics

3.1 Introduction

The recent 2007-09 financial crisis, driven by the plummeting land prices, has led to a contraction in credit supply and an ongoing prolonged slump in economic output, business investment and employment. During the financial crisis, 40%-90% of one years' output was foregone (Atkinson et al. 2013), the employment ratio decreased from 63% in 2007 to 58% in 2009 (Mian & Sufi 2014), constrained firms had deep cuts in capital spending (Campello et al. 2010). U.S. housing prices plummeted, which had a significant impact on the firms' financial activities as most of corporate loans were secured by the pledgable collateral (Berger & Udell 1990). In particular, Reinhart & Rogoff (2009) show that a substantial part of the costs from financial crises is a slow trajectory of economic growth.[1] How do firms respond to the shocks in the credit market due to the sharp decline in collateral value? Do financial crises result in a temporary slowdown of corporate behavior or exert a long-lasting adverse impact? Do the presence of financial and real frictions impedes the speed of asset recovery and are the growth paths influenced by the status of the firms? This chapter attempts to shed light on the above questions.

[1] See also Reinhart & Rogoff (2014) and Papell & Ruxandra (2012) for evidence of slow economic growth and protracted economic recession.

The collapse of the U.S. real estate market has generated a substantial interest in understanding the link between collateral value and the firms' real outcomes via the collateral-based lending channel (e.g., Kiyotaki & Moore 1997, Gan 2007, Chaney et al. 2012, Liu et al. 2013, Ersahin & Irani 2017). In an environment where a firm's borrowing capacity is subject to collateral constraints due to the limited enforcement,[2] the price of collateral assets affects the value creditor can recover upon default. It hence affects the amount of debt borrowers can obtain to finance their factor demands. Liu, Wang & Zha (2013) show that real estate comprises a large proportion of collateral asset and Zhang et al. (2017) find that banks reduce their lending significantly as a result of the residential property market collapse.[3] Therefore, the fluctuations in the housing market may spill over to the firms' real-side outcomes by affecting the access to credit via the collateral constraints. Empirical researchers face challenges in establishing the link between financial (credit supply) shocks and real outcomes as credit market disruptions are always accompanied by the weakening of business demands for credit. Moreover, the presence of capital market imperfections can propagate and amplify the shocks from the real economy (e.g., productivity shocks) during the crisis (Bernanke et al. 1999), which makes it hard to disentangle the shocks in the financial sector from the shocks in the real economy.

My model is built on DeAngelo et al. (2011) with an extension of labor market frictions and shocks from the financial (collateral-based) sector. The dynamic structural model features the firm's optimal investment policy, employment choice and financing decisions. The model includes two sources of disturbances: productivity shocks, individual and aggregate, as well as collateral shocks, which affect the liquidation value of capital recovered by the lender upon default. I attempt to disentangle the effect of credit supply shocks from credit demand shocks by modelling productivity

[2]Studies suggesting that firms must pledge collateral to secure the promises to pay and the ability to do so can enlarge the firms' debt capacity include Berger & Udell (1990), Jimenez et al. (2006), Eisfeldt & Rampini (2008), Benmelech & Bergman (2009), Chaney et al. (2012), Rampini & Viswanathan (2010)

[3]Huang & Stephens (2015) also discuss the effect of housing market on the reduction of credit availability.

and collateral shocks as two independent random processes. The model embeds a rich set of real frictions and financial frictions. When firms adjust their capital stock, they are subject to capital adjustment costs and investment irreversibility under which it is more costly to cut capital than to expand it. More importantly, I incorporate frictions from the labor market, i.e., costs from changing labor input and inability to adjust wages. Firms are subject to financial frictions when they finance their factor demand with costly external financing, i.e., debt and equity, when their internal funds are depleted. Debt capacity is limited by collateral constraints and a negative shock in collateral value reduces the firms' ability to borrow. Equity financing entails costs arising from asymmetric information problems and security flotations.

The model shows that an adverse shock to the collateral value leads to a large and protracted decline in output level, capital stock, employment, firm value and the resulting recovery is slow and does not revert to the pre-shock level over a long horizon. Investment and net borrowing experience a steep decline upon the impact. The response to the collateral shock, however, is mitigated when the economy is hit by a productivity (demand) shock simultaneously. When the business demand is depressed during the financial crisis, the negative impact of credit supply shortage (collateral-driven) is substantially mitigated as the firms have lower financing needs. The interaction between these two types of shocks manifests the challenge faced by the empirical researchers to disentangle the effect of credit supply from the firms' demand for credit. The contraction of the firms' activity during the crisis can not be purely ascribed to a shock from the supply-side when it is accompanied by a demand-side shock.

I examine whether the negative economic outcomes depend on the types of shocks and the status of firms. In particular, I conduct comparative statics to examine how the impact of different shocks changes with the nature of financial and labor market frictions. Firstly, I show that debt issuance drops (i.e., is procyclical) when either an adverse productivity shock or collateral shock hits. Equity issuance increases with the negative collateral shock (countercyclical) and decreases with the negative productivity shock (procyclical). The cyclicality of equity financing depends not only on the types of shocks, but also the financial status of firms. The adverse collateral shock leads to a larger increase of equity issuance for financially unconstrained firms (firms with lower equity issuance costs) as they are in a better position to offset the negative impact on the debt capacity during the worsening of credit conditions by selling equity. For investment decisions, consistent with Hennessy & Whited (2007), I show that the costs of equity financing dampen the response of investment to the productivity shock. Secondly, I find that lowering labor adjustment costs fares better for small firms than for large ones. Also, firms with costless labor adjustment cut investment and hiring less aggressively following a collateral shock, however, they choose to shed workers or stop hiring and reduce their investment to a greater extent in the face of depressed business demands, i.e., when the negative productivity shock hits.

The remainder of the chapter is structured as follows. Section 3.2 outlines the literature mostly related to my work. Section 3.3 shows a overview of the recent financial crisis in the US. Section 3.4 describes the benchmark model and provides analysis for the firms' optimal decisions. Section 3.5 discusses the model calibration and model solution before plotting the policy functions. Section 3.6 studies the implications of the productivity shock and the collateral shock. Section 3.7 performs comparative statics and analyzes how the firms' responses to the shocks vary by the firm types and the nature of frictions. Section 3.8 draws conclusions.

3.2 Related literature

This chapter contributes to various strands of literature in corporate finance, financial crises and labor economics. First, I add to a growing body of research in an effort to explore the link between financial crisis and real economy. More specifically, by exploring the channel of collateral constraints, I give a role to the shocks originating from the financial sector in explaining the steep decline and the slow recovery in real outcomes. The important challenge posed to the analyses of financial crisis is the separation of credit supply effect from its demand effect. A small set of papers try to address the link through the demand effect. Bernanke, Lown & Friedman (1991) point out that failing credit demand during the credit crunch caused much of the slowdown of economy. Mian & Sufi (2012) point to the aggregate demand channel in accounting for significant job loss and Mian, Rao & Sufi (2013) support the household demand view as leveraged households decrease their spending drastically after the collapse of housing prices.[4] On the other hand, some authors argue that shocks from credit supply played a more crucial part in triggering the macroeconomic effect of the crisis (e.g., Peek & Rosengren 2000, Dell'Ariccia et al. 2008, Kroszner et al. 2007, Braun & Larrain 2005) and in influencing the firm-level decision (e.g., Campello et al. 2010, Almeida et al. 2012, Duchin et al. 2010, Chodorow-Reich 2013). There is a long-standing effort in macroeconomics and corporate finance which aims to examine the role of credit market imperfections in propagating the shocks originating from the real economy, e.g., productivity shocks.[5] However, the importance of shocks originating from the financial sector has begun to receive attention only recently. Ajello (2016) maintain that the shocks to the financial intermediation costs can explain most of the business fluctuations. My paper follows in the spirit of Jermann & Quadrini (2012), Khan & Thomas (2013), Liu et al. (2013) and Zetlin-Jones & Shourideh (2017) in that I model credit supply shock as a shock to the collateralized borrowing constraints and examine their impact on the real and financial behavior. Jermann & Quadrini (2012) and Liu et al. (2013) do not differentiate among different types of firms and assign no role to the frictions stemming from the real-side activities such as wage rigidities, labor market frictions and investment irreversibility. Khan & Thomas (2013) and Zetlin-Jones & Shourideh (2017) both argue that financial shocks can generate a misallocation of capital and a disruption to the measured aggregate productivity.

[4]See also Eggertsson & Krugman (2012),Iacoviello (2005), Iacoviello & Neri (2010), Guerrieri & Lorenzoni (2017) for the household demand view.

[5]One example of macroeconomic literature is Bernanke et al. (1999) in which credit market imperfections such as asymmetries of information can act as "financial accelerator" and propagate, mostly amplify, the shocks to the real economy. Hennessy & Whited (2007) show that firm-level investment respond less aggressively to the profit shocks in the face of high equity financing costs.

By assuming that resource reallocation following the financial shocks is the driving force behind the variations in product demand, these papers face the difficulties in separating the effect of credit supply from the demand effect. Moreover, both of them focus on the contraction in borrowing and pay little attention to the alternative source of financing, i.e., equity, as firms are able to substitute away from debt financing with equity issuance. And my framework departs from theirs in the sense that I characterize endogenous borrowing limits by taking into account the ability of investment to relax the collateral constraints in the current period.

At the same time, this chapter builds on the previous attempts to explain the prolonged nature of economic recessions. Cerra & Saxena (2008) find that output loss from financial crises persists even at the ten-year horizon. Reinhart & Rogoff (2009) show that the negative impact of financial crises is highly persistent with housing market collapse lasting for over six years on average. Unemployment spikes on average lingers for five years. Reinhart & Rogoff (2014) study 100 systemic banking crises and find that it takes around eight years for output level to reach the pre-crisis level. Theoretically, Khan & Thomas (2013) show that the credit shocks lead to a slow recovery of GDP during the financial crisis via increased capital and productivity reallocation, although leaving the weak growth of investment and employment unexplained. I consider a full range of real frictions and financial frictions, i.e., labor market frictions and the costs of equity financing, and gauge the extent to which each of the frictions contributes to the decline and the gradual recovery of corporate activities. I also deviate from Khan & Thomas (2013) as I examine the role of collateral shocks without triggering a deterioration in aggregate productivity. By evaluating the reaction of different kinds of firm, my work is close to Zetlin-Jones & Shourideh (2017) in that I show that the importance of financial and real frictions varies by the firm types.

Second, the chapter adds to the extant literature by assigning a central role to collateral in the understanding of corporate investment, employment and leverage decisions. The plummeting of the housing market at the onset of the financial crisis underlines the importance of collateral channel as it curtails the borrowing capacity of a firm by affecting the lender's ability to repossess collateral. Chaney et al. (2012) and Gan (2007) show that an adverse shock to collateral value leads to a substantial drop in investment. Schmalz et al. (2017) argue that an rise in collateral value can increase the chance of starting up a new business. Ersahin & Irani (2017) discover that firms increase employment in response to the appreciation of real estate values. Rampini & Viswanathan (2010) argue that firms subject to collateral constraints may choose to engage in risk management and conserve debt capacity and Rampini & Viswanathan (2013) and Campello & Giambona (2013) find that asset tangibility, or redeployability, has important implications for firm's capital structure decisions. More recently, Li et al. (2016) find that collateral constraints are of central importance as they create incentives to preserve debt capacity. My work, relying on the framework of a financial crisis, abstracts from the prior studies that firms curtail their spending on capital and labor when credit tightens as a result of the fall in collateral value.

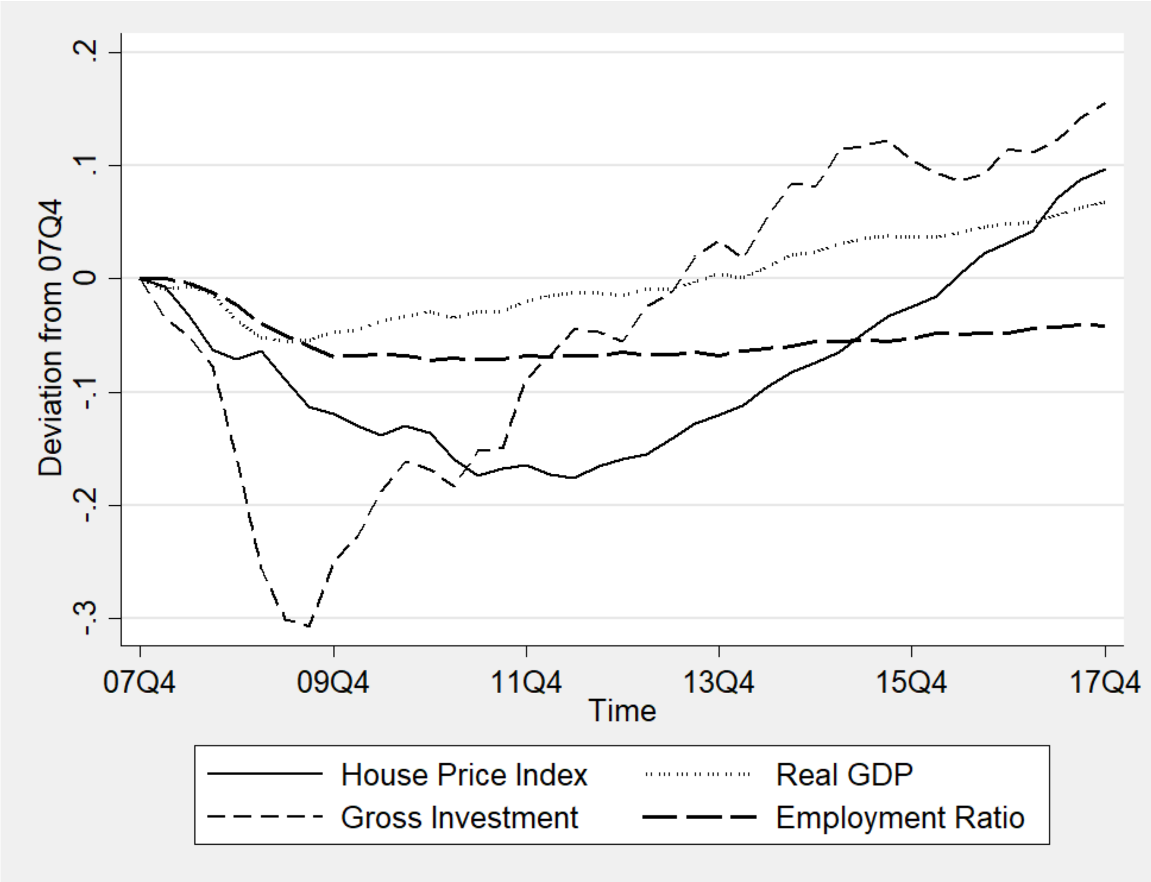
Third, this work is related to the literature on financial constraints and labor. Monacelli et al. (2011) argue that the credit contraction leads to a sluggish recovery of unemployment as lower debt allows the workers to bargain for higher wage in recessions. Michaels et al. (2016) show that increased cost of funds reduce employment and labor earnings. On the empirical side, Chodorow-Reich (2013) find that firms with pre-crisis unhealthy lenders reduce their employment by more. Duygan-Bump et al. (2015) show that credit supply shocks cause more employees working for firms dependent on external finance to lose their jobs. Caggese et al. (2016) find that financial frictions distort firms' hiring decision. I model reduced borrowing capacity due to the tightening collateral constraints as a conduit for the firms to downsize their labor force and examine how the relationship varies with the nature of labor market frictions.

3.3 Overview of the 2007-09 financial crisis

The 2007-09 financial crisis was associated with a steep decline in economic activities and a protracted nature of the collapse. Figure 3.1 plots the percentage change from

2007Q4 of real GDP, all-transactions house price index (estimated using sales prices and appraisal data), gross private domestic investment and employment-to-population ratio. The movement of real GDP at the beginning was small and the largest drop was observed in 2009Q2, in which real GDP declined by 5.5% compared to 2007Q4. The GDP recovered slowly and reverted to the pre-crisis level in 2013Q4. The house price as represented by the house price index from the Federal Housing Finance Agency exhibited a significant and persistent deterioration. The house price index continued to drop until 2012Q2 and did not move back the pre-crisis boom until 2016Q3. The greatest decline of house price index came late and amounted to around 18% in 2012Q2. Gross private domestic investment experienced a steep decline. It dropped by 30% in 2009Q3 and returned to the 2007Q4 level in 2013Q3. Employment-to-population ratio decreased from 62.8% in 2007Q4 to 58.3% in 2010Q4. It remained at low state and did not revert to the pre-crisis level even until 2017Q4.

Figure 3.1: An overview of economic activities in 2007-09 recession



Note: Figure 3.1 plots the time-series evolution of main economic variables after the 2007-09 financial crisis. Real GDP per capita, gross investment are extracted from Bureau of Economic Analysis (BEA). All-Transactions House Price Index is drawn from Federal Housing Finance Agency. Employment-to-population ratio is obtained from Bureau of Labor Statistics (BLS). All series are plotted as percentage change from the level in 2007Q4.

To understand the link between credit market and real corporate outcomes, I examine the impact of financial crisis on the firm-level investment and employment. The decrease in the supply of credit should hinder investment (employment) when the firms' accessible funds fail to meet their investment (employment) demands. The effects of credit constraints are more severe for firms with high target level of investment. For firms lacking profitable investment opportunities and having lower demands for funds, the shortage of external financing becomes less of a concern. I compare the investment and employment growth of firms with different levels of pre-shock investment opportunities before and after the onset of the crisis by employing a differences-in-differences strategy. In order to divide the sample into pre-crisis and post-crisis period, I extract quarterly data from Compustat between 2007 and 2017 and adjust the fiscal year a quarter ahead. In August 2007, American Home Mortgage Investment Corporation files for Chapter 11 bankruptcy protection, which propagates the collateral shocks to the financial institutions [6]. Therefore, I identify the post-crisis episode as the periods after the last quarter of 2007. Specifically, I define year 2007 (pre-crisis period) as the last quarter in 2006 (fiscal quarter with an end-date after October 1, 2006) and the first three quarters in 2007 (fiscal quarter with an end-date before October 1, 2007). The rest (between the last quarter in 2007 and the end of 2017) is defined as the post-crisis period. The estimation is on an annual basis. I exclude financial firms (SIC between 6000 and 6999), utility firms (SIC between 4900 and 4999) and public administration (SIC between 9000 and 9999). I discard firm-year observations that have sales/asset growth higher than 100% and drop observations with sales or capital stock less than 1 million USD to eliminate the effect of outliers. I measure investment as capital expenditure scaled by gross property, plant and equipment at the beginning of the year. I control for firm-specific characteristics by including firm fixed effects, Q and cash flow. Q is defined as the beginning-of-year market of book of asset ratio (see Appendix 3.B for the details of constructing Q) and cash flow is the sum of income before extraordinary item and depreciation scaled by beginning-of-year gross capital stock. As the data for employment size is only available in the annual file, I define the pre-crisis period as the fiscal year 2007 for the estimation of employment growth. Employment growth is the percentage change of current employment from employment in the previous year. Dummy variables for the post-crisis period ($After$) are created and I also generate dummies for each of the post-crisis year to study the long-run impact. High-Q is an indicator equal to one for the firms that are in the top quartile of pre-crisis Q distribution.

[6] See https://www.stlouisfed.org/financial-crisis/full-timeline for the discussion of the timeline for financial crisis

Table 3.1: Effects of crisis on investment and employment growth

The table presents the results:

$$\text{Inv}_{it} = \beta_0 + +\beta_1 Q_{it-1} + \beta_2 CF_{it} + \beta_3 After + \beta_4 After \times \text{High-}Q + \eta_i + \epsilon_{it} \quad (1)$$

$$\text{Emp}_{it} = \beta_0 + \beta_1 Q_{it-1} + \beta_2 CF_{it} + \beta_3 After + \beta_4 After \times \text{High-}Q + \eta_i + \epsilon_{it} \quad (2)$$

$$\text{Inv}_{it} = \beta_0+\beta_1 Q_{it-1}+\beta_2 CF_{it}+\gamma_1 D2008+\gamma_2 D2009+\ldots+\theta_1 D2008\times\text{High-}Q+\theta_2 D2009\times\text{High-}Q+\ldots+\eta_i+\epsilon_{it} \quad (3)$$

$$\text{Emp}_{it} = \beta_0+\beta_1 Q_{it-1}+\beta_2 CF_{it}+\gamma_1 D2008+\gamma_2 D2009+\ldots+\theta_1 D2008\times\text{High-}Q+\theta_2 D2009\times\text{High-}Q+\ldots+\eta_i+\epsilon_{it} \quad (4)$$

Inv is capital expenditure scaled by beginning-of-year gross capital stock. Emp is the percentage change of current employment from employment in the previous year. Q is the ratio of market value to book value of asset at the beginning of the year. CF is the sum of income before extraordinary item and depreciation scaled by beginning-of-year gross capital stock. $After$ is an indicator equal to one for the post-crisis period. D_n represents dummies for the year n. High-Q is an indicator equal to one for the firms that have pre-crisis Q higher than 75th percentile of the distribution. Firm fixed effects η_i are included in the regressions. (High-Q is measured only once per firm, therefore the firm fixed effects subsume the effects of High-Q.) Standard errors are clustered at the firm level (shown in the parenthesis). Adjusted R square and the number of observations are also reported. ***, **, *indicate significance at the 1%, 5% and 10% levels.

Independent variables:	Investment:		Employment growth:	
	(1)	(2)	(3)	(4)
$After$	-.042***		-.033***	
	(0.004)		(0.005)	
$After$ ×High-Q	-.027**		-.021**	
	(0.014)		(0.01)	
$D2008$		-.005		-.049***
		(0.006)		(0.006)
$D2009$		-0.049***		-0.075***
		(0.005)		(0.006)
$D2016$		-0.074***		-0.048***
		(0.006)		(0.006)
$D2017$		-0.081***		-0.042***
		(0.006)		(0.006)
$D2008$×High-Q		-0.02		-0.005
		(0.017)		(0.013)
$D2009$×High-Q		-.042***		-0.03**
		0.016		0.013
$D2016$ ×High-Q		-0.029*		-0.05***
		(0.016)		(0.014)
$D2017$×High-Q		-0.02		-0.046***
		(0.016)		(0.014)
Q	.031***	.029***	.028***	.026***
	(0.003)	(0.003)	(0.004)	(0.004)
Cash flow	.001	.001	0.007***	0.006***
	(0.003)	(0.003)	(0.002)	(0.002)
Firm fixed effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.500	0.513	0.198	0.217
Obs.	17342	17342	23298	23298

Table 3.1 tabulates the estimation output. Column (1) shows that there is a decline in investment following the onset of the crisis for and the decline is 2.7% greater for firms that report high Q in the pre-crisis period. Column (2) shows that investment for low-Q firms in 2008, 2009, 2016 and 2017 is 0.5%, 4.9%, 7.4% and 8.1% smaller than the reference year (2007). The coefficient for 2008 dummy is not significant, indicating a delayed decline for investment. The coefficients on the 2016 and 2017 dummies are significantly negative, showing that the effect of 2007-09 financial crisis are still present after a decade. The investment has not recuperated to the pre-crisis level even in the most recent years. Again, the negative coefficients on the interaction terms between 2009 dummy and High-Q show that the drop is more severe for firms with better investment opportunities and, thus, higher financing demands. Column (3) and (4) examine the behavior of the firms' employment. There is an immediate significant drop in employment growth following the onset of the crisis. Similar conclusions are drawn for employment growth that the negative response to the credit supply shock is more pronounced for the firms with a high level of pre-shock investment opportunities. In addition, for employment growth, the gap from the pre-crisis level in the recent years is still significant.

3.4 The general model

This section describes my theoretical framework. The model features heterogeneous firms with different sizes, financial positions, and idiosyncratic productivity. There are three control variables: the capital stock, the labor force and the one-period debt (net of cash). The model includes two sources of uncertainties: productivity shocks (aggregate and idiosyncratic) and collateral shocks which affect the liquidity value of capital.

3.4.1 Technology

The Cobb-Douglas production function where the firm uses capital K and labor input N to produce output is given by:

$$Y(Z_t, X_t, K_t, N_t) = Z_t X_t (K_t^{\alpha} N_t^{1-\alpha})^{\theta},$$

where α controls the relative share of two inputs and θ controls the degree of returns to scale. With $0 < \theta < 1$, this production function displays decreasing returns to scale. X_t is the aggregate state variable that summarizes the technology and consumer demand conditions in the general economy (see, for example, Bertola 1998). Z_t describes the firm-specific productivity. Both X_t and Z_t are informative about the financing demand of the firm. The aggregate productivity and idiosyncratic productivity are independent of each other and evolve according to the log AR(1) process

$$\log(X_{t+1}) = \rho_x \log(X_t) + \sigma_x \varepsilon_{t+1}^x, \quad \log(Z_{t+1}) = \rho_z \log(Z_t) + \sigma_z \varepsilon_{t+1}^z,$$

in which ε_{t+1}^x (also ε_{t+1}^x) are i.i.d. disturbance terms with standard normal distribution. The AR coefficient ρ_x (ρ_z) denotes the persistence level of aggregate (firm-specific) productivity. Denote the corporate tax rate as τ. The operating cash flow is

$$\Pi(Z_t, X_t, K_t, N_t, \bar{w}_t) = (1 - \tau) \left(Y(Z_t, X_t, K_t, N_t) - \bar{w}_t N_t \right) + \delta_k \tau K_t,$$

where $\bar{w}_t$ is the average wage rate, δ_k is the constant rate of capital depreciation and $\delta_k \tau K_t$ is the depreciation tax shield. The law of motion for the firm's labor force N_t is governed by

$$N_{t+1} = (1 - \delta_n)N_t + H_t,$$

where δ_n is the quit rate and H_t denotes the gross hires, which is positive if the firm is hiring and negative if the firm is firing. The firm bears the cost of hiring labor such as the fees of advertising and posting vacancies, screening candidates and training staff. The cost of labor adjustment, denoted by $C(H_t)$, is

$$C(H_t) = c^h H_t \mathbf{1}_{\{H_t \geqslant 0\}},$$

where c^h is the cost of hiring per worker. Although it is costless for the firms to shed workers, the labor adjustment cost motivates the firm to hoard labor as it is costly to reverse the decisions and hire them back. This creates a region of inaction where firms choose not to hire or fire labor. Wage $\bar{w}_t \equiv w$ under the full wage rigidity where the wage remains homogeneous for all workers in any periods of time (new labor is being hired at the same wage as the current employees and the wage remains constant indefinitely). The importance of wage rigidities is emphasized in a broad set of literature. Stiglitz (1984) attempts to explain wage rigidities as a consequence of implicit insurance provided to the risk-averse employees or a substitute for the lower productivity brought by the lower wage. Empirically, Shimer (2004) shows that the introduction of rigid wage accounts for the large fluctuations of employment and vacancies (see also Pischke (2018), among others). Daly & Hobijn (2014) document that the fraction of workers with no wage change increased substantially in 2011 relative to 2006 (see also Fallick et al. (2016), among others). I also look at the flexible wage contract where firms can adjust wages for the new hires based on the spot market rate and keep the same wages for incumbents for a certain period. I follow the wage setting in Favilukis & Lin (2015). For the current employees, they face the probability of $1 - u$ to have their wages reset. In other words, I allow the firm to reset the wage for the new hires according to the spot wage w_t and pay the same wage for current employees for $\frac{1}{1-u}$ periods. In this way, the wage in each period will also depend on the number of new employees endogenously chosen by the firm. The number of incumbents is given by $Inc_t = (1-\delta_n)N_t + H_t\mathbf{1}_{\{H_t<0\}}$ and the number of new hires is given by $H_t\mathbf{1}_{\{H_t>0\}}$. The average wage of the firm is a weighted average of the previous average wage and the spot wage:

$$\overline{w_{t+1}} = \frac{(1-u)Inc_t w_{t+1} + uInc_t\overline{w}_t + w_{t+1}H_t\mathbf{1}_{\{H_t>0\}}}{N_{t+1}}.$$

This wage setting captures the important implications of Haefke et al. (2013) that the wages of newly hired workers are more cyclical and more responsive to the labor productivity. Similar to Belo et al. (2014), I assume that the spot wage is an increasing function of the aggregate productivity and aggregate collateral value. It is given by

$$w_t = \kappa_0 \exp(\kappa_1 \log(X_t) + \kappa_2 \log(S_t)), \tag{2.E.1}$$

where $\kappa_0 > 0$ and $0 < \kappa_1 < 1$, $0 < \kappa_2 < 1$. S_t denotes the value of collateral asset which would be explained in details later. In this specification, κ_1 and κ_2 measure the elasticity of wage to the aggregate productivity and the value of collateral asset. $0 < \kappa_1 < 1$ and $0 < \kappa_2 < 1$ capture the fact that wage, though cyclical, is less volatile than the aggregate state variables.

The law of motion for the firm's physical capital stock K_t is governed by

$$K_{t+1} = (1-\delta_k)K_t + I_t,$$

where δ_k is the depreciation rate and I_t is the gross investment, which is positive if the firm is investing and negative if the firm is disinvesting. I normalize the price of buying capital to 1. If the firm sells the used capital, it only recovers the price of $p^s < 1$. The assumption that resale price of used capital is lower than purchase reflects the frictions of capital investment due to the irreversibility. It creates the region of inaction whereby the firm is cautious about making investment as the decision is difficult to be reversed. Also, capital investment incurs both convex and fixed adjustment costs. Therefore, the total costs of capital adjustment are specified as

$$G(I_t, K_t) = (a^k K_t + I_t)\mathbf{1}_{\{I_t \geqslant 0\}} + p^s I_t \mathbf{1}_{\{I_t < 0\}} + \frac{\gamma}{2}(\frac{I_t}{K_t})^2 K_t.$$

p^s is the resale price of capital. a^k is the parameter for fixed capital adjustment costs to capture the notion of lumpy investment (Cooper & Haltiwanger 2006, Whited 2006). I denote the parameter for convex adjustment costs as γ to account for the investment smoothness. The indicator function $\mathbf{1}_{\{I_t(.) \geqslant 0\}}$ equals one if the firm is making positive investment.

3.4.2 Financing

As in DeAngelo et al. (2011), the firm can finance its factor demand with internal funds, one-period discount bond and external equity. Denote the stock of net debt as B_t. B_t is allowed to take negative value, indicating cash holding. Also I include the tax benefit of debt as the interest accrued to the debt is tax deductible, thus debt is preferred to equity (pecking order theory). The interest payment of debt after tax is $r(1-\tau)B_t$. Unlike in Gamba & Triantis (2008), there is no debt issuance cost. Hence, the firm never simultaneously hold cash and debt and any positive amount of cash will be used to reduce debt outstanding before issuing the new one.

Due to the limited enforcement of contracts between lenders and firms, the firm faces collateral constraints when borrowing. It requires that the promised debt payment does not to exceed the liquidation value of the collateral, which is pledged by the firm when issuing debt with tangible capital. The collateral constraint the firm faces is

$$B_{t+1}(1 + r(1-\tau)) \leqslant S_t(1-\delta_k)K_{t+1}.$$

Recall that a negative value of B_{t+1} represents a positive net cash position and a positive value represents a positive net debt position. S_t denotes the value of collateral and it lies between 0 and 1. To explore the implications of collateral shocks, I let S_t follow

$$\log(S_{t+1}) = \mu_s + \rho_s \log(S_t) + \sigma_s \varepsilon^s_{t+1},$$

where μ_s determines the mean level of collateral value and the stochastic innovations ε^s_{t+1} denote collateral shocks which lead to unexpected changes to the collateral variable S_{t+1}.

I define dividend to the equity holders as

$$e_t = \Pi(Z_t, X_t, K_t, N_t, \bar{w}_t) - G(I_t, K_t) - C(H_t) + B_{t+1} - B_t(1 + r(1-\tau)).$$

If $e_t > 0$, the firm is making dividend distributions to equity holder. If $e_t < 0$, the firm is issuing equity to cover the financing shortfall. Equity issuance incurs security flotation costs and adverse selection costs due to asymmetric information problems (Myers & Majluf 1984). I define the cost to external equity financing as a linear-quadratic function (Riddick & Whited 2009):

$$\psi(e_t) = (-\eta_0 + \eta_1 e_t - \frac{\eta_2}{2} e_t^2)\mathbf{1}_{\{e_t<0\}},$$

in which $\eta_i > 0$, $i = 0, 1, 2$. $\mathbf{1}_{\{e_t<0\}}$ is the indicator function which is equal to one when the firm is issuing equity. The firm chooses $(K_{t+1}, N_{t+1}, B_{t+1})$ each period to maximize the expected discounted value of future cash flow given the current firm capacity, financial position, productivity level and collateral value. Define the state space vector as $\Omega_t \equiv (Z_t, X_t, S_t, K_t, N_t, B_t, \bar{w}_t)$. The equity value satisfies the following Bellman equation:

$$V(\Omega_t) = \max_{K_{t+1}, N_{t+1}, B_{t+1}} \{e_t + \psi(e_t) + \beta \mathbb{E}_t[V(\Omega_{t+1})]\}, \tag{2.E.2}$$

where $\beta = 1/(1+r)$ is the discount factor and the expectation is taken by integrating over the conditional distribution of S_t, X_t and Z_t. The first two terms represent the immediate cash inflow/outflows and the third term represents the continuation value of the firm.

3.4.3 Optimality conditions

This subsection develops the optimality conditions for each of the firm's choices. I derive the optimal policy assuming that wage is constant and does not enter the state space vector. Let $\lambda \equiv \lambda_t$ be the current-value Lagrange multiplier associated with the collateral constraints. The first-order condition for investment policy (K_{t+1}) is: [7]

$$G_I(I_t, K_t)\big(1 + (\eta_1 - \eta_2 e_t)\mathbf{1}_{\{e_t<0\}}\big) = \beta\mathbb{E}_t[V_K(\Omega_{t+1})] + \lambda(1-\delta)S_t. \tag{2.E.3}$$

The left-hand side represents the cost of installing additional unit of capital. It encompasses the cost of capital adjustment (real frictions) and cost of tapping equity financing (financial frictions). The existence of financial costs temper the response of investment to the shocks from economy. According to Hennessy & Whited (2005), the envelope condition for $V_K(\Omega_t)$ is $V_K(\Omega_t) = \big((1-\tau)Y_K(.) + \delta_k\tau - G_K(.) + (1-\delta_k)(1 + G_I(.))\big)\big(1 + (\eta_1 - \eta_2 e_t)\mathbf{1}_{\{e_t<0\}}\big)$. The right-hand side is the marginal value for capital, which includes collateral value of investment in relaxing the borrowing constraints. The first-order condition with respect to labor choice (N_{t+1}) is:

$$C_H(H_t)\big(1 + (\eta_1 - \eta_2 e_t)\mathbf{1}_{\{e_t<0\}}\big) = \beta\mathbb{E}_t[V_N(\Omega_{t+1})]. \tag{2.E.4}$$

Eqn (2.E.4) equates the marginal cost of expanding labor with the future net benefits contributed by this unit of labor. Expanding or downsizing labor today requires cost of labor adjustment as seen in $C_H(H_t)$. The envelope condition for $V_N(\Omega_t)$ is $V_N(\Omega_t) = \big((1-\tau)Y_N(.) - w + (1-\delta_n)C_H(H_t)\big)\big(1 + (\eta_1 - \eta_2 e_t)\mathbf{1}_{\{e_t<0\}}\big)$. Lastly, I solve

[7] Based on the value function (2.E.2), I can specify the Lagrange formulation as:

$\mathcal{L}_t = e_t + \psi(e_t) - \lambda_t\big(B_{t+1}(1+r(1-\tau)) - \xi S_t K_{t+1}\big) + \beta\mathbb{E}_t\{V(\Omega_{t+1}) - \lambda_{t+1}\big(B_{t+2}(1+r(1-\tau)) - \xi S_{t+1}K_{t+2}\big) + \ldots\}$.

Take first derivative with regard to K_{t+1} (or I_t), one can arrive at (2.E.3).

for the optimality condition for debt. The first derivative with respect to B_{t+1} is:

$$1 + (\eta_1 - \eta_2 e_t)\mathbf{1}_{\{e_t<0\}} = -\beta\mathbb{E}_t[V_B(\Omega_{t+1})] + \lambda(1 + r(1 - \tau)), \tag{2.E.5}$$

where the envelope condition has that $V_B(\Omega_t) = -\big(1+r(1-\tau)\big)\big(1+(\eta_1-\eta_2 e_t)\mathbf{1}_{\{e_t<0\}}\big)$.[8] The left-hand side captures the value of debt as financing with equity incurs costs. The right-hand side represents the expected marginal cost of debt financing. The first term on the right side is the costs of issuing debt as it incurs after-tax interest payment next period, which is more costly if the firm has to issue equity to serve it. The second term on the right-hand side represents the costs of debt stemming from the collateral constraints. This term captures the opportunity cost of issuing debt today rather than preserving debt capacity to issue tomorrow should better projects arise. It also creates incentives for firms to hold cash or pay down debt to free up debt capacity for future funding needs as equity financing entails costs (DeAngelo et al. 2011).

3.5 Model calibration and solution

The solution of the model must be obtained numerically. I first calibrate the model to reproduce the moments on the firm-level data. And I examine the economics behind the model by simulating the policy functions.

3.5.1 Calibration

The calibration of the model relies on parameter values used in related articles such as Hennessy & Whited (2007), Gamba & Triantis (2008), Gilchrist et al. (2014) and

[8]With the envelop condition and the first-order condition for debt (2.E.5), I can derive the following the shadow value of relaxing borrowing constraints

$$\lambda_t = \frac{1}{(1 + r(1 - \tau))}(\eta_1 - \eta_2 e_t)\mathbf{1}_{\{e_t<0\}} - \beta\mathbb{E}_t[(\eta_1 - \eta_2 e_{t+1})\mathbf{1}_{\{e_{t+1}<0\}}].$$

For simplicity, I ignore the script t for λ throughout the paper.

Jermann & Quadrini (2012). In contrast to Gilchrist et al. (2014) and Jermann & Quadrini (2012), my model solution is at the annual frequency rather than the quarterly frequency. The quarterly frequency will dramatically lower the computation speed. Based on Figure 3.1, the impact of the financial crisis has not receded even over the horizon of ten years, therefore I opt for yearly frequency to accelerate the convergence speed of the solution algorithm due to the multi-dimensionality. The baseline parameters governing the process of individual productivity are similar to those in Gamba & Triantis (2008), which is $\rho_z = 0.6$, $\sigma_z = 0.15$. The parameter set for the aggregate productivity shock is yearly adjusted based on Jermann & Quadrini (2012) and Gilchrist et al. (2014) such that $\rho_x = 0.8$ and $\sigma_x = 0.04$. The persistence level ρ_s is set at 0.885, a value adjusted according to the estimates in Gilchrist et al. (2014) using the price index of used car sales. This indicates a half-life of 5.7 years and accords with the house price index and used vehicle sales index in U.S. published by U.S. Federal Housing Finance Agency and U.S. Bureau of the Census, which shows that it takes around nine years for the price indices to return to the pre-crisis level. σ_s is set at 0.06, which is the average estimate of standard deviation in Jermann & Quadrini (2012) and Gilchrist et al. (2014). $\mu_s = -0.0797$, which indicates that the steady-state liquidation value of collateral is 0.5. It is chosen such that a steady-state ratio of the book leverage is 50% (Gilchrist et al. 2014). The capital share α_k is set to be 0.36, the same as Belo et al. (2014). The returns to scale θ is set as 0.8. For simplicity, I look at a more general tax scheme. The tax rate for debt interest payment is $\tau = 0.25$, which is assumed to the tax rate on cash and on corporate earnings.

To set the parameters for capital adjustment and labor adjustment, I follow Michaels et al. (2016) and Cooper & Haltiwanger (2006). The resale price of capital is lower than its purchase price and is set at 0.7. The fixed cost of capital adjustment is $a^k = 0.04$ based on the estimates in Cooper & Haltiwanger (2006). I set the parameter γ to be 0.06, showing that one additional dollar of investment is associated with 0.009 dollar installation costs. The depreciation rate δ_k is set at 0.14 to replicate the mean level of investment rate. As for the labor hiring costs, I take the values from Michaels et al. (2016) and set $c^h = 0.08$. The quit rate δ_n is set at 18% to match the monthly quit rate of around 1.5% for manufacturing industries from BLS (Bureau of Labor Statistics).

The parameter for the equity financing function is set according to the estimates in Hennessy & Whited (2007). The fixed cost of issuing equity is set at $\eta_0 = 0.598$. The linear and quadratic cost parameters for equity issuance are set at $\eta_1 = 0.05$ and $\eta_2 = 0.0004$. According to the underwriting fee scheme shown in Hennessy & Whited (2007), the value set implies that the firm faces a proportional fee equal to 0.047 on the first dollar of gross proceeds.

Appendix 3.A summarizes the calibrated parameters for the benchmark model. For simplicity, I assume wage is constant when performing the model calibration. Table 3.2 presents firm-level moments from the actual data and moments computed from the simulated data of the model. The details of data construction are presented in Appendix 3.B.
The value function $V(\Omega_t)$ and the optimal policy function are solved using value function iteration method. To smooth the results, multidimensional linear interpolation is used extensively in solving for the policy function and value function. After I solve the model, I begin to simulate an artificial cross-section of 2000 firms with 150 model periods. The simulation begins by taking one random path for X_t and S_t and 2000 random paths for Z_t. I remove the first 120 periods to eliminate the impact of initial suboptimal conditions. The simulation procedure is repeated 500 times.

3.5.2 Simulated policy functions

Using the calibrated parameters, I evaluate the key choice variables in the model by presenting the policy functions in Figure 3.2. The solid (dashed) line in the left panel plots the investment rate (defined as I_t/K_t), employment growth (defined as H_t/N_t) and net debt issuance rate (defined as $B_{t+1} - (1+r)B_t/K_t$) in response to the aggregate productivity level X_t when S_t is fixed at intermediate state (low state).

Table 3.2: Target moments

This table summarizes the empirical and model-implied firm-level moments calculated on an annual basis. The accounting data is drawn from a sample of non-financial, non-utility and unregulated firms in Compustat industry annual file between 1990 and 2006. While employment size is drawn from Compustat, wage data comes from Quarterly Workforce Indicators (QWI) of the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau. QWI data is merged with Compustat based on their 4-digit NAICS industry code, the state of headquarters and the size of employment. Investment spike is defined if the investment rate is 2 times greater than its mean.

Moment	Data	Model
Investment rate	0.144	0.149
Std. dev. of investment rate	0.144	0.138
Frac. of investment spikes	0.114	0.131
Serial Corr. of investment rate	0.580	0.660
Employment growth	0.031	0.046
Std. dev. of employment growth	0.233	0.319
Wage bills/asset ratio	0.318	0.304
Dividend/asset ratio	0.010	0.029
Income/asset ratio	0.112	0.179
Std. dev. of income/asset ratio	0.164	0.083
Serial Corr. of income/asset ratio	0.798	0.523
Market-to-book ratio	2.242	2.312
Frac. of negative dividends	0.532	0.522
Equity issuance/asset	0.044	0.060
Frac. of negative debt	0.323	0.333
Debt issuance/asset	0.0077	0.0077

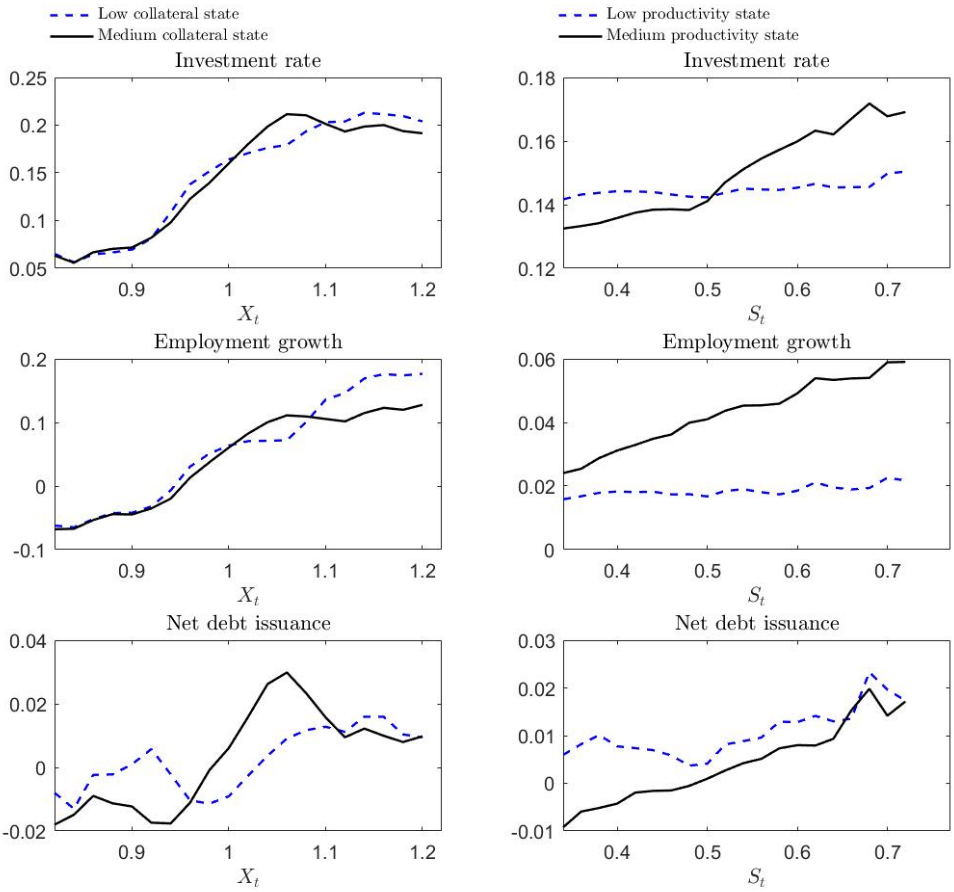
The solid (dashed) line in the right panel plots the choice variables in response to the collateral level S_t when productivity X_t is fixed at intermediate state (low state). Investment rate and employment growth initially rises steeply with X_t but then flattens out. The constraints on the borrowing imposed by the limited value of S_t causes the stagnation. Net debt issuance summarizes the behavior of saving (negative value) and borrowing from lenders (positive value). With low level of aggregate productivity, firms save but the saving decreases with X_t initially as liquid assets are shifted to more

[8]Due to some statistical error, the investment rate at high X_t for the medium collateral state is slightly lower than that for the low collateral state. Also the low collateral state might lead to lower K_t, which results in a higher I_t/K_t.

productive uses should productivity rise due to the mean-reverting nature of the shock (see Riddick & Whited (2009) for the explanation of the substitution effect). The saving starts to rise with the aggregate productivity under a slightly higher level of X_t due to the income effect generated by X_t. With high level of aggregate productivity, firms increase their borrowing with the productivity X_t initially. Then the increase in borrowing is bounded by the collateral constraints and firms even reduce the debt outstanding with sufficient internally-generated funds brought by the high productivity level (income effect). The response does not change by much even if the collateral value is low.

With regard to the response to the collateral value, both real variables and financial variables rise slowly but monotonically with S_t when the productivity level is intermediate. Nonetheless, the low level of productivity generates a modest response to S_t for all variables. Fluctuations in credit supply have an impact on firms' policy only when firms have sufficient financing demands (i.e., productivity level is sufficiently high). The corresponding response of investment rate and employment growth underlines the importance of the collateral-driven credit channel in explaining the change of real policies and how the credit channel interacts with the demand (productivity) channel.

Figure 3.2: Simulated policy functions



The solid line (dashed line) of left panel in Figure 3.2 plots the response of investment, employment growth and debt issuance (net of cash) to the aggregate productivity (X_t) when S_t is kept at median (low) level. The solid line (dashed line) of right panel in Figure 3.2 plots the response of investment, employment growth and debt issuance (net of cash) to the aggregate collateral variable (S_t) when X_t is kept at median (low) level.

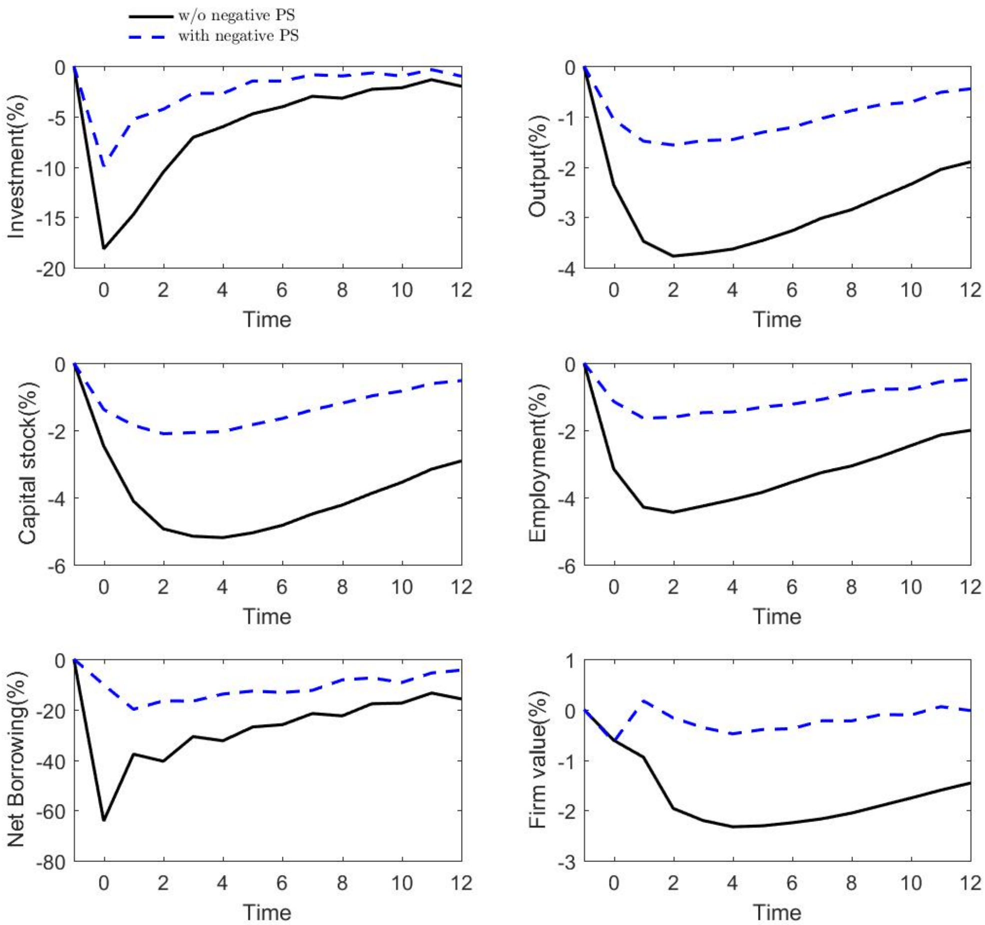
3.6 Implications of aggregate shocks

In this section, I assess the firms' policies in response to the aggregate productivity and collateral shocks. In each simulation, a negative collateral (productivity) shock hits in period 0 and leads to a drop in collateral value (aggregate productivity). I intend to study the key choice variables and firm value in response to the negative shocks. I compute the model-implied impulse response functions and plot the value of investment, capital stock, employment stock, output level, net debt and firm value upon the impact. In this section, I focus on the case where the wage is fully rigid.

Figure 3.3 shows how the firms' policies respond to the shocks to the aggregate collateral value. The solid line describes the response to a single shock in collateral variable S_t when the aggregate productivity variable X_t is fixed at its intermediate level. A shock to the collateral value leads to 16% decline in S_t (1.5 standard deviation), which mimics the deepest percentage decline in the house price during the financial crisis. I assume that the wage is rigid and insensitive to the aggregate state variables ($\kappa_2 = \kappa_1 = 0$) in this case. Upon the impact of the collateral shock, investment plunges sharply by more than 15%, in line with the sharp decrease observed for the business investment at the onset of the financial crisis. The adverse collateral shock results in a large and persistent deterioration in the output level, capital stock and employment. The output, capital stock, and employment gradually decline and the resulting recovery is slow and remain below the pre-crisis level for a prolonged period. The effect on the financial leverage is translated into 60% drop in the net borrowing and stays below the pre-shock level over the response period. The total firm value continues to fall upon the impact and the following pick-up is subdued.

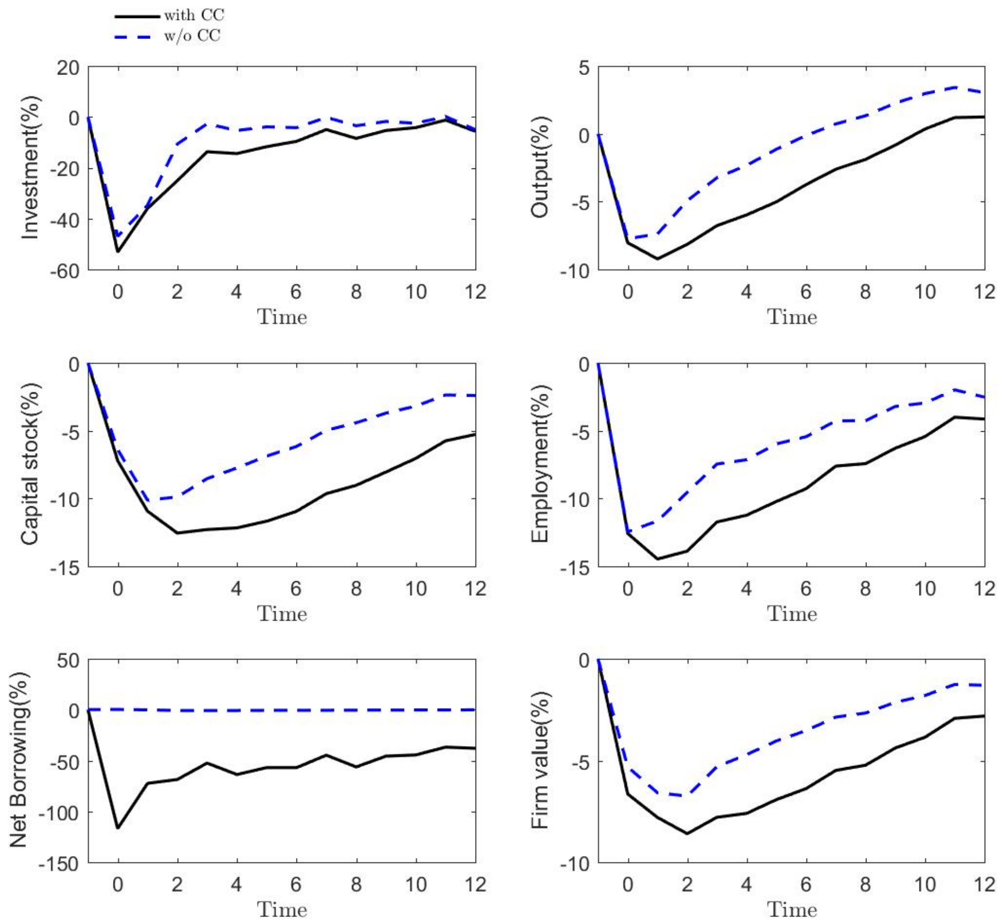
The dotted line in Figure 3.3 illustrates the response to the collateral shock when the economy is struck by an adverse productivity shock as well. To isolate the impact of collateral shock, I first model the responses when both shocks hit and then take the difference in responses between the twin shocks and the single productivity shock. For instance, investment rate drops by 60% when both negative shocks strick the economy and by 50% when a single adverse productivity shock hits. One can only ascribe 10% of the decline in the investment rate to the impact from the collateral sector. It shows that when the productivity is depressed during the financial crisis, the firms have less financing needs and the influence of negative collateral shock on real and financial variables will be less pronounced. The muted response to the collateral shock translates into a slight drop in firm value and a rapid and full recovery thereafter. This result stresses a important interaction between the shock from credit demand and

Figure 3.3: Response to the collateral shock



Note: Figure 3.3 describes the impulse response functions for investment, output level, capital stock, employment, net debt and firm value. A shock reduces the collateral value by 1.5 standard deviation upon the impact. The solid line depicts the movement of variables in response to the collateral shock when aggregate productivity is fixed at the median level. The dotted line describes the effect of the collateral shock when both shocks hit by taking the difference in response between the twin shocks and the single productivity shock. The collateral value is allowed to revert to the long-run level after the shock. The y-axes depict the percentage change (difference in percentage change for the dotted line) from the pre-shock level.

Figure 3.4: Response to the aggregate productivity shock



Note: Figure 3.4 describes the impulse response functions for investment, output level, capital stock, employment, net debt and firm value. In both lines, a shock reduces the aggregate productivity by 1.0 standard deviation upon the impact and collateral variable is fixed at the long-run mean level. Solid line depicts the case with collateral constraints (with CC) and dashed line depicts the situation without collateral constraints (w/o CC). The aggregate productivity is allowed to revert to the long-run level after the shock. The y-axes depict percentage change from the pre-shock level.

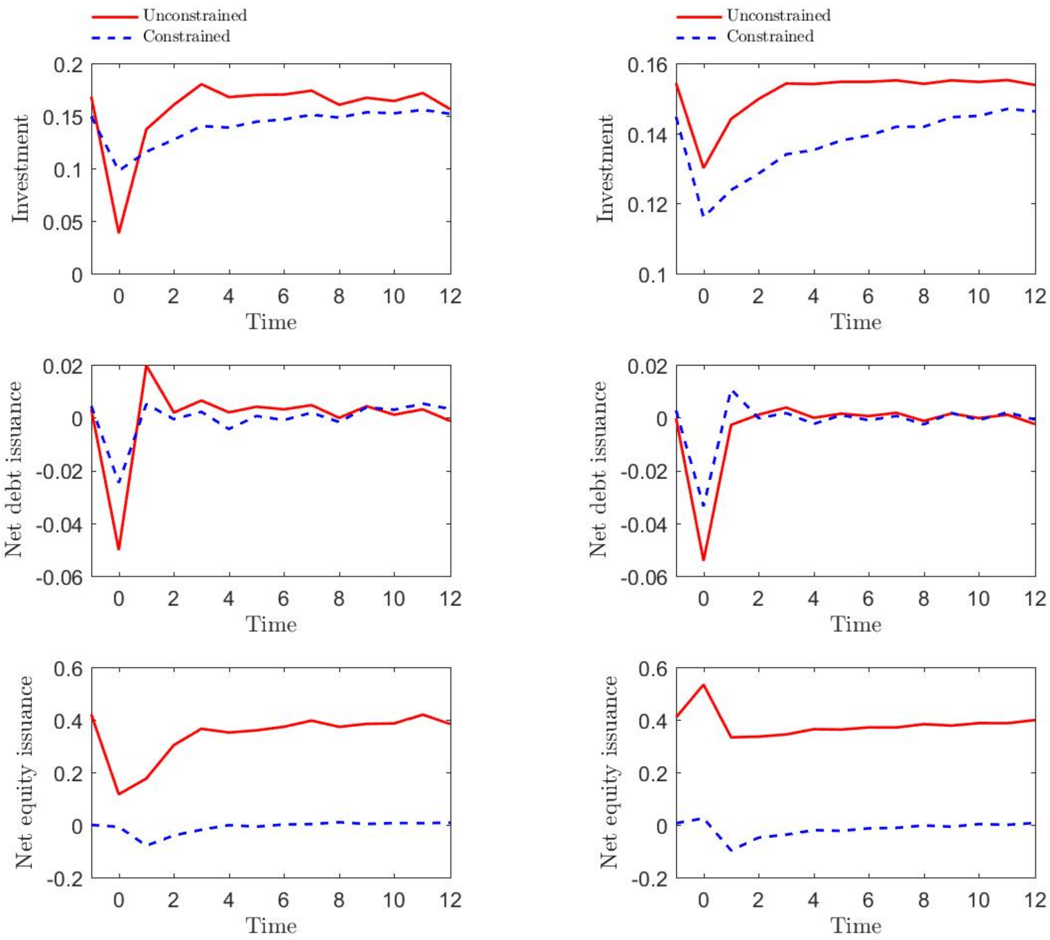
credit supply. The credit supply shock exerts a significant impact on the firm's real and financial policies only when productivity or demand remains at the steady state (as compared to a dip in productivity since the crisis). This finding represents the challenge researchers face in identifying and isolating the impact of credit supply shock from its demand effect. The impact of supply shock subsides when the demand-side effect of the crisis dominates during economic downturns. In this case, any destruction to the firms' activities during the downturns can not be purely ascribed to the shocks from the supply side. Therefore, the crisis episode used to identify the impact of the credit supply shock must not coincide with the weakening of business conditions. The firms' long-run behavior when hit by the aggregate productivity shock is shown in the solid line of Figure 3.4. A shock to the aggregate productivity (S_t is kept at its median) corresponds to 6% drop in X_t, which replicates the percentage drop in GDP during the crisis. It induces a substantial drop in all of the economic variables in response to the decline in credit demand. Investment and output gradually bounce back to full capacity over the response period. After the initial drop, firm value steadily improves over time, contrasting the slow growth of firm value displayed when collateral shock hits. The dashed line describes the situation when the firm is not bounded by the collateral constraints. When the collateral constraints do not exist, the firm would increase the debt capacity to the largest possible level to take advantage of tax benefits. Sharp decline is still observed for the real variables, but the magnitude is smaller and non-binding constraints allow the firm to revert to the pre-shock level at a slightly faster pace.

3.7 Comparative statics: financial frictions and labor market frictions

This section presents the comparative static results that demonstrate how firms' behavior changes with the nature of frictions of equity financing and labor market when impacted by a shock. Figure 3.5 compares firms with high equity financing costs (constrained) with firms that face zero equity financing costs (unconstrained). I define constrained firms as the firms which face twice the benchmark parameter values in terms of linear and quadratic equity financing costs. The solid line depicts the response of variables to the shock when there are no equity issuance costs (unconstrained) and the dotted line describes the response of variables to the shock when the equity financing is costly (constrained). It plots the evolution of net debt issuance, net equity issuance, investment with an adverse productivity shock (Figure 3.5a) or an adverse collateral shock (Figure 3.5b). The investment of an unconstrained firm (a firm with zero equity financing costs) is better safeguarded against the impact of collateral shock and recovers at a higher speed. The shock to aggregate productivity translates into a larger decline in investment but a stronger recovery in the financially unconstrained scenario. The unconstrained access to equity financing allows firms to accommodate their investment in response to emerging business opportunities more flexibly. When the firms are burdened with high equity financing costs, investment falls less steeply with the productivity shock. Constrained firms anticipate high equity issuance costs associated with a strong funding need in the future to scale back investment when the productivity rises (mean-reverting nature). As it is costly to reverse investment decisions due to the presence of external financing costs, constrained firms would cut down on investment less aggressively. This is in line with Hennessy & Whited (2007), who show that the presence of costly external finance dampen the response of investment to the productivity. Net debt issuance collapses when either shock strikes, which corresponds to the procyclicality of debt financing evidenced in the economic literature (Covas & Den Haan 2011, Jermann & Quadrini 2012). Constrained firms cut

Figure 3.5: Comparative statics of financial frictions on the response to the shocks

(a) Response to the productivity shock (b) Response to the collateral shock



Note: Figure 3.5 describes the impulse response functions for net debt issuance, net equity issuance and investment, all scaled by capital stock. The solid line depicts the response of variables to the shock when there are no equity issuance costs. The dotted line describes the response of variables to the shock when the equity financing is costly. A shock reduces the collateral value (aggregate productivity) by 1.5 (1.0) standard deviation upon impact. The collateral value (aggregate productivity) is allowed to revert to the long-run level after the shock.

debt issuance less significantly as it may incur higher costs of equity issuance to build up leverage for tax benefits in the future. The cyclical nature of equity issuance depends on the types of shocks and the financial status of firms. The negative productivity shock causes the equity issuance to fall (i.e., procyclical) while the negative collateral shock causes the equity issuance to rise (countercyclical) initially. The productivity shock case, as shown in Figure 3.5a, reveals that equity issuance decreases in response to the diminished demand for financial funds. But the response is modest for financially constrained firms with their equity issuance suppressed. Also the constrained firms would save rather than pay dividends (negative equity issuance) to avoid the potential costly equity issuance. The collateral shock case shows that firms substitute debt financing for equity issuance when the negative shock to the collateral value curtails the borrowing capacity. Such substitution effect and thus the countercyclical nature of equity issuance with respect to the collateral shock are amplified for firms that have an easier access to the equity financing market. Covas & Den Haan (2011) argue that the cyclicality of equity issuance depends on firm sizes and only large firms display countercyclical equity issuing behavior. I show that firms with lower equity financing costs are in a better position to offset the negative impact on the debt capacity during the worsening of credit conditions by selling equity.

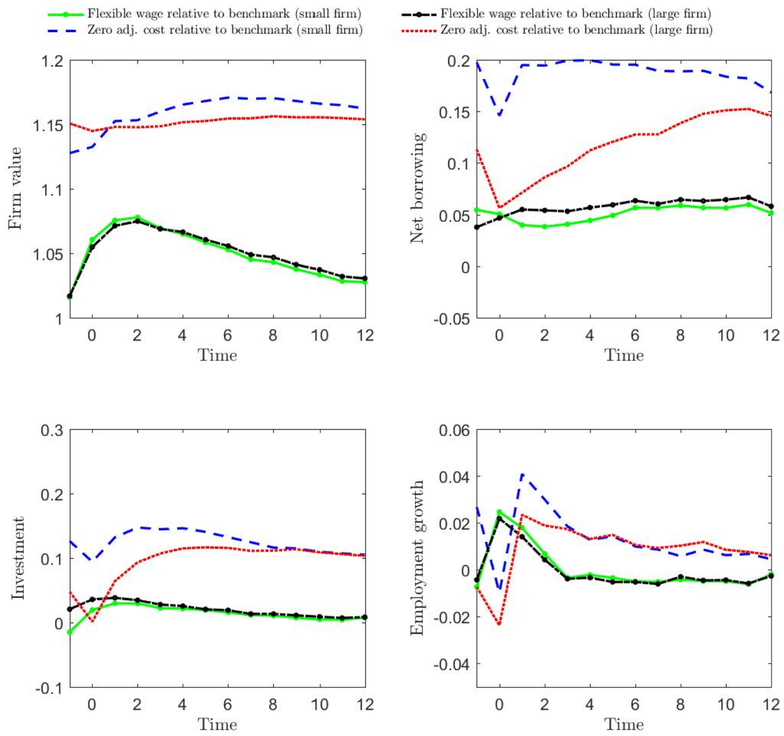
According to the labor hoarding concept (Biddle 2014), costs from adjusting labor input, e.g., transaction costs of new hiring, training costs, acquiring skills, prevent firms from optimizing their employment behavior flexibly and instantaneously. Also, firms operating in industries with powerful labor unions have less flexility to fire workers and hire workers with caution as it is difficult to unwind such a decision (Chen et al. 2011). Hence, adjusting wages while retaining the working force during economic contractions would allow firms to recover faster when business revives. On the other hand, firms may face difficulties in adjusting wages and the resulting optimization strategies lead to laying off workers, which makes wage rigidities become a well-documented driving force for high unemployment rates and large employment fluctuations (see, e.g., Hall 2005, Mian & Sufi 2014, Pischke 2018). To examine these two sources of labor rigidities,

Figure 3.6 demonstrates the relative value of wage flexibility and relative value of costless labor adjustment (contractual term flexibility) for both large firms and small firms. The relative firm value is computed as firm value in the flexible case scaled by the firm value in the benchmark case. The relative value of net debt issuance, investment and employment growth are computed as the difference in value between the flexible case and the benchmark case.[9] The firms that have costless labor adjustment ($c^h = 0$) can embrace the flexibility of hiring and also shedding workers. I sort the firms based on their capital stock (K_t) one period before the shock. Small (large) firms are the firms that are in the bottom (top) 30% of the distribution of capital stock in that period. In the wage contract setting shown in Eqn (2.E.1), κ_2 controls the elasticity of wage to the aggregate collateral variable and is set at 0.1. κ_1 controls the elasticity of wage to the aggregate productivity and is set at 0.3. It indicates that a negative shock to the collateral value or to the productivity is associated with around 1.7% drop in the spot wage rate w_t. The wage for the newly hired workers is set according to the spot wage rate and the wage for the incumbents is adjusted with the probability of $1-u$. u is set at 0.6 in the analyses, indicating that the current employees will have their wage changed every 2.5 periods. The marked solid (marked dashed-dotted) line in Figure 3.6 plots the total value, net debt issuance, investment and employment growth of small (large) firms under flexible wage contract relative to the rigid wage contract case. The dashed (dotted) line in Figure 3.6 plots the total value, net debt issuance, investment and employment growth of small (large) firm under zero labor adjustment costs relative to the costly labor adjustment (flexible connatural terms) case.

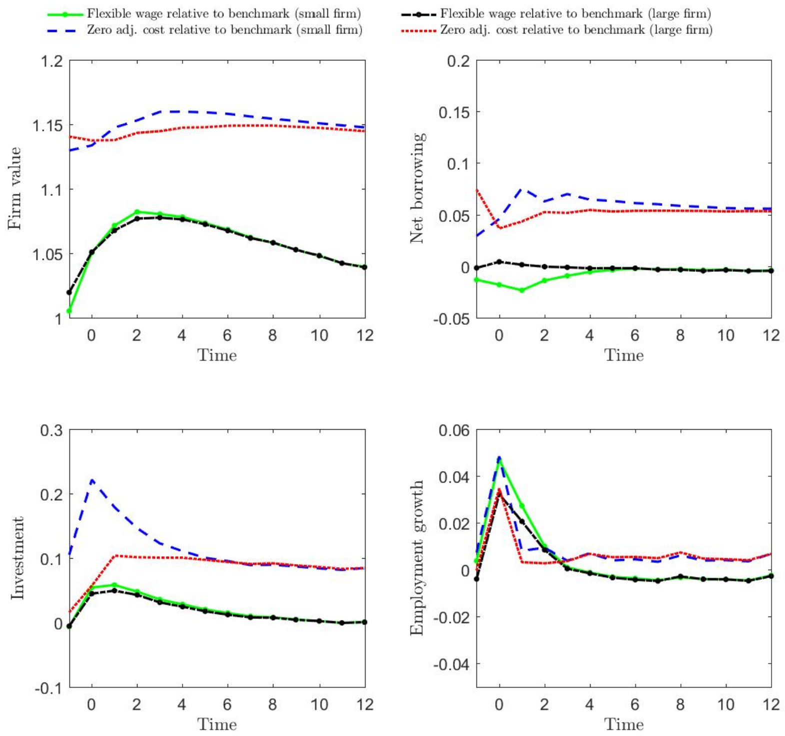
[9] I choose not to scale in this case to avoid the impact of negative value.

Figure 3.6: Comparative statics of labor market frictions on the response to the shocks

(a) Response to the productivity shock



(b) Response to the collateral shock



Note: Figure 3.6 shows the relative value of wage flexibility and the relative value of costless labor adjustment upon the impact of negative productivity shock and collateral shock. The relative firm value is computed as firm value in the flexible case scaled by the firm value in the benchmark case. The relative value of net debt issuance, investment and employment growth are computed as the difference in value between the flexible case and the benchmark case. The marked solid (marked dashed-dotted) line plots the total value, net debt issuance, investment and employment growth of small (large) firms under flexible wage contract relative to the rigid wage contract. The dashed (dotted) line plots the total value, net debt issuance, investment and employment growth of small (large) firm under zero adjustment costs relative to the costly labor adjustment. A shock reduces the collateral value (aggregate productivity) by 1.5 (1.0) standard deviation upon impact. The collateral value (aggregate productivity) is allowed to revert to the long-run level after the shock. The y-axes depict the value relative to the benchmark case.

Several features stand out from Figure 3.6. Firstly, costless labor adjustment is far more important for small firms than for large ones. Note that an initial upward (downward) trend of relative value indicates that the value in the flexible case drops by less (more) upon the negative impact and the subsequent upward (downward) trend indicates that the value recovers faster (slower) when the condition reverts. As shown in the top left graph in Figure 3.6a and Figure 3.6b, the relative firm value under costless labor adjustment increases steadily for small firms within the 5-year horizon after the impact of either shock, which implies that the total firm value of small firms with zero labor adjustment frictions drop by less initially when negative shocks hit and revives to the trend level at a higher pace. The relative level of net borrowing with zero labor adjustment costs rises for small firms while decreases for large firms upon the impact of negative collateral shock, which implies that net borrowing of small firms decreases less dramatically if the labor adjustment costs are lowered. Cross-sectionally, for the most part, the dashed line stays above solid line for investment and employment growth, meaning that the additional level of investment and hiring brought by a flexible labor contractual term is higher for small firms than for large firms. Small firms are more likely to engage in active hirings to expand their business, therefore the value of lowering labor adjustment costs is manifested more for small firms than for large firms in handling the adverse shocks.

Secondly, firms with costless labor adjustment cut their investment and employment activities by less following a collateral shock, however, they reduce their investment and employment activity to a greater extent when productivity shock hits. As shown in the bottom graph in Figure 3.6b, the relative value measured in terms of investment and employment growth [10] brought by the costless labor adjustment rises initially upon the impact of collateral shock, indicating that firms will cut down on their investment and hiring activity less aggressively if they bear no labor adjustment costs. After the firms' financial conditions are worsened by the collateral shock, firms with costly

[10] Recall that the relative value in this case is calculated as the difference in investment (employment growth) between firms with costless labor adjustment and firms with costly labor adjustment costs.

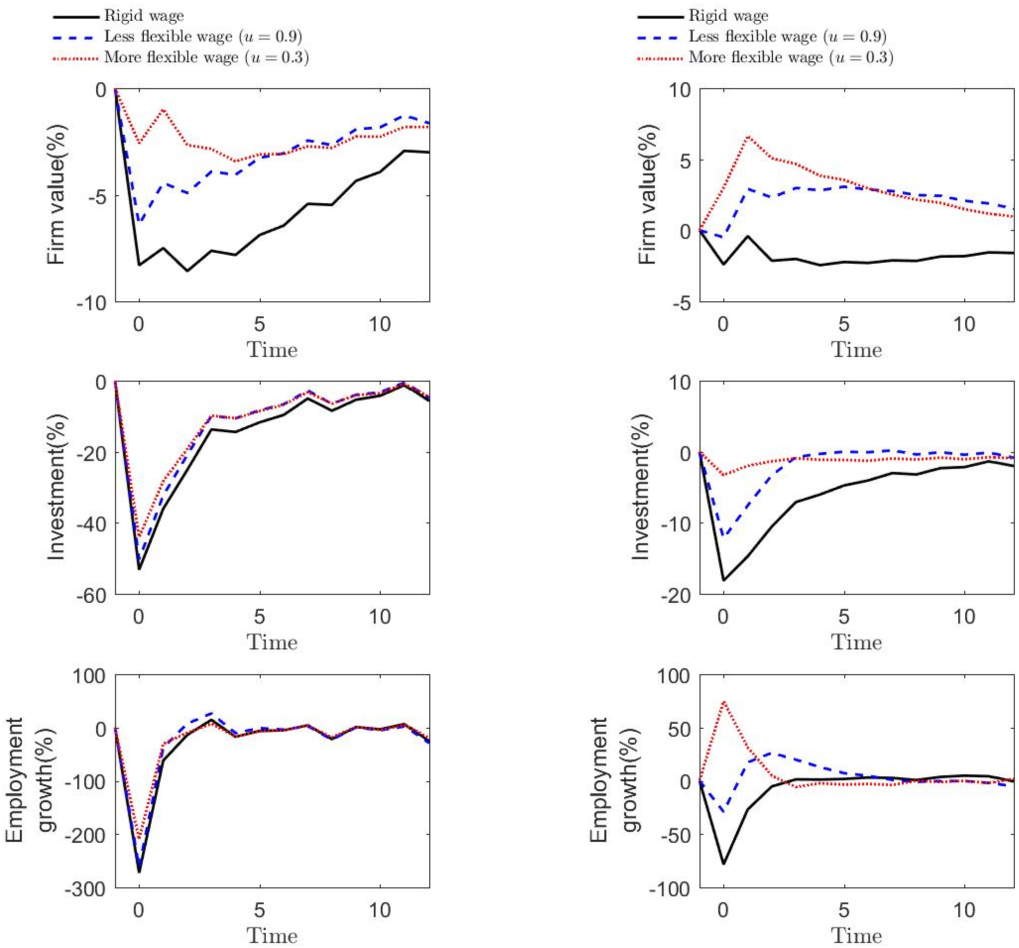
labor adjustment see a larger decline in employment growth as replacing the workers who quit incurs costs and is constrained by the availability of financing. If the labor adjustment costs are trimmed, firms are able and willing to replenish the labor force as the productivity and labor demand remain robust. Nonetheless, as shown in the bottom graph in Figure 3.6a, the relative value of costless labor adjustment measured in terms of investment and employment growth falls upon the impact of productivity shock, indicating that firms cut their investment and employment activities *more* significantly. In this case, firms choose to fire workers or cut hiring and slash their investment as a response to a depressed business demand, and they are more able to do so with lower labor adjustment costs as they know that they can unwind the decision easily when business demand bounces back.

Thirdly, flexible wage contract alleviates the short-run negative impact of *both* shocks and allows both firm value and the level of real activity to deteriorate on a smaller scale than in the case of their rigid wage, regardless of the firm size.[11] For a better clarification, I provide the impulse response functions with regard to different level of wage flexibility in Figure 3.7. The initial mitigation brought by the flexible wage to the firms' investment and employment policy is more pronounced with the shock from the collateral sector. The alleviation from flexible wage being less apparent for firms suffering from a productivity shock shows that it is optimal for firms to scale down their economic activities facing a productivity slowdown, even at a lower wage rate. The difference between flexible wage and rigid wage case narrows down through time when X_t (S_t) is returning to its long-run level. It means the firms with flexible wage will curtail their investment and shed their workers less dramatically and also see their firm value fall by a lower extent. However, the value of flexible wage diminishes over time as the wage starts to rise with the recuperating economy.

[11] Though the changes in wage should exhibit a higher impact on firms that have large employment size (large firms), I find that the wage is more rigid for large firms than it is for small firms as large firms are less likely to involve themselves in new hiring.

Figure 3.7: Response to the shocks with different wage settings

(a) Response to the productivity shock (b) Response to the collateral shock



Note: Figure 3.7 describes the impulse response functions for firm value, net borrowing, investment and employment growth. The solid line describes the situation where the wage is the same for all employees (incumbents and new hires) in any periods of time. The dashed line and the dotted line describes the situation where wage for the new hires is set at the spot wage rate. The level of wage flexibility is modulated by u. $u = 0.9$ ($u = 0.3$) indicates that the wage for the incumbents can be reset at the probability of 0.1 (0.7).

3.8 Conclusions

The 2007-09 financial panic was accompanied by a steep and protracted slump in house value and economic activities. It arguable provides an episode for researchers to assess the long-run effect of a credit supply shock. However, it poses a challenge as the credit crunch is followed by the worsening of business demand. I build a structural model in which the productivity (demand) shock and credit supply (collateral) shock is modeled as two independent random processes. Also, I examine whether the responses to the shocks depends on the types of shocks and the status of firms.

I find that a negative shock to the collateral value, which results in tightening the credit constraints, can lead to a protracted recession and subdued recovery with real business conditions (aggregate productivity) unchanged. Nonetheless, the impact of credit supply shock subsides when the demand-side takes effect - a slump in the productivity. The importance of cutting labor adjustment costs is manifested more in small firms than in large ones. The reduction of labor adjustment costs causes investment and employment growth to fall more dramatically with the negative productivity shock but decline less significantly with the negative collateral shock. The negative outcomes from the collateral shock are substantially tempered for firms that sign a flexible wage contract. As a matter of financial decisions, I find that equity issuance is procyclical with the productivity shock and countercyclical with the collateral shock. The cyclicality of equity financing is less pronounced for financially constrained firms.

Appendix *3.A.* Benchmark parameters

The parameter values used in the calibration of the benchmark model are presented in Table *3.A.*1.

Table *3.A.*1: Key calibrated parameters

Parameters	Value
Technology: Production	
Returns to scale (θ)	0.8
Share of capital in the production function (α)	0.36
Rate of depreciation (δ_k)	0.14
Quit rate of labor (δ_n)	0.18
Technology: Adjustment costs	
Resale price of capital (p^s)	0.7
Convex parameter in capital adjustment costs (γ)	0.06
Fixed parameter in capital adjustment costs (a^k)	0.04
Hiring cost per capita (c^h)	0.08
Financial functions	
Fixed cost of equity financing (η_0))	0.598
Linear cost of equity financing (η_1)	0.05
Quadratic cost of equity financing (η_2)	0.0004
Stochastic process	
Persistence of the idiosyncratic productivity process (ρ_z)	0.6
Volatility of the idiosyncratic productivity process (σ_z)	0.15
Persistence of the aggregate productivity process (ρ_x)	0.8
Volatility of the aggregate productivity process (σ_x)	0.04
Persistence of the collateral value (ρ_s)	0.885
Volatility of the collateral value (σ_s)	0.06
Steady-state collateral value (μ_s)	-0.0797

Appendix *3.B.* Data variables

In this appendix, I provide some details regarding the calculations of the target moments. The sample is extracted from Compustat industry annual file incorporated in the U.S. between 1990 and 2006. I discard the financial firms (SIC between 6000 and 6999), utility firms (SIC between 4900 and 4999) and government services (SIC between 9000 and 9999). Inside the parenthesis, I write data name in Compustat industry annual file. Investment is measured as capital expenditure ($capx$). Capital stock is defined as gross property, plant and equipment ($ppegt$). Investment rate is constructed as capital expenditure scaled by capital stock. Investment spike is defined if the investment rate is 2 times greater than its mean. Market-to-book of ratio is defined as market value of asset (the market value of asset is market value of common stock ($prcc\_f \times csho$) plus total asset (at) minus total common equity (ceq) minus deferred taxes ($txdb$)) divided by total value of book asset (at). Employment growth is defined as the percentage change in the number of staff (emp). Dividend is the sum of common dividend and preferred dividend. Income is defined as operating income before depreciation ($oibdp$). Total debt is long-term debt ($dltt$) plus debt in current liabilities (dlc). Net debt is total debt net of cash (che). Equity issuance is the sale of common and preferred stock ($sstk$). I also delete the firms that have sales or asset growth exceeding 100% to eliminate the effect of business discontinuities. I drop the observations with sales or capital stock less than 1 million USD to eliminate the effect of outliers. I winsorize all relevant variables at 1% in each year. Wage data comes from Quarterly Workforce Indicators (QWI) of the Longitudinal Employer-Household Dynamics (LEHD) program at the U.S. Census Bureau. I obtain the average earnings of employees with stable jobs who work for the private non-farm companies. QWI data is then merged with Compustat based on their 4-digit NAICS industry code, the state of headquarters and the size of employment. Wage bills is labor earnings multiplied by employment.

Chapter 4

Revisiting the measurement error in q: An investigation of the covariance among regressors

4.1 Introduction

Tobin's q and cash flow are the common explanatory variables in empirical corporate finance research to study how investment or other variables of interest responds to the growth opportunities and the internal financial resources. There is a large body of empirical literature that places Tobin's q and cash flow on the right-hand side when performing the OLS regressions. Fazzari, Hubbard & Petersen (1988) have examined the effect of internal funds on investment by linearly regressing investment on Tobin's q and cash flow (see also, e.g., Rauh 2006, Lamont 1997). Following Fazzari, Hubbard & Petersen (1988), investment-cash flow sensitivity has been employed to gauge the degree of financial constraints (Goyal & Yamada 2004, Erel et al. 2015), to examine the role of stock market valuations in determining investment spending (Blanchard et al. 1993, Campello & Graham 2013), to investigate the impact of labor frictions on corporate behavior (Chen & Chen 2013, Benmelech et al. 2011) and to analyze the effect of managerial characteristic (Bertrand & Schoar 2003, Malmendier & Tate 2005) and ownership structure (Hadlock 1998, Pindado et al. 2011) on corporate decision making. More importantly, a number of studies attempt to challenge the positive and even monotonic relationship between financing constraints and investment-cash flow sensitivity (Kaplan & Zingales 1997, Cleary 1999, Gomes 2001, Chen & Chen 2012). Moreover, papers that study a firm's saving behavior also draw conclusions based on regressions with Tobin's q and cash flow (Almeida et al. 2004, Bates et al. 2009). This poses a challenge as empirical Tobin's q is measured with error and researchers are struggling to come up with a better empirical proxy.

Despite the measurement error in the empirical q variable, OLS regressions with q and cash flow as the right-hand-side variables are prevalent in the realm of corporate finance. Among the empirical research that employs both Tobin's q and cash flow as regressors, several major findings stand out. Chen & Chen (2012) find that investment-cash flow sensitivity decreases over time and disappears in the late 2000s (Brown & Petersen 2009, Moshirian et al. 2017). Cross-sectionally, Hadlock & Pierce (2010) suggest that more financially-constrained firms as indicated by having high WW index, KZ index and HP index can have *lower* investment-cash flow sensitivity. However, a fundamental concern in the OLS regressions arises due to the measurement error contained in the observed empirical Tobin's average q (mismeasured variable). The measurement error leads to inconsistent estimates on other correlated variables such as cash flow and any inference drawn from the biased estimates is potentially incorrect. Concerns about biases resulting from measurement error are discussed in Erickson & Whited (2000, EW hereafter). EW (2000) argue that the observed positive investment-cash flow sensitivity may be spurious as the measurement error in empirical q biases cash flow coefficient estimates upward from its theoretical prediction of zero derived based on the first order conditions in Lucas & Prescott (1971) and Mussa (1977).

We find, via the classical errors-in-variables model, that the sign of covariance between q (mismeasured variable) and cash flow (perfectly-measured variable) plays an important role in shaping the way measurement error affects the estimates of cash flow coefficients in an OLS regression. We show that both cash flow sensitivity of investment and cash flow sensitivity of cash demonstrate a declining pattern over time (See also Chapter 2 of this thesis). Based on the errors-in-variables model, the measurement error in q biases the OLS estimates of cash flow upward only if q and cash flow have a significant positive covariance, denoted as $\phi_{Qcf} > 0$. As the variance-covariance structure between cash flow and q varies over time, this variation may offer an explanation for the discrepancies of cash flow sensitivity in different periods. We discover that the ϕ_{Qcf} in the late periods are negative or non-significantly positive. The negative correlation between cash flow and investment opportunities as proxied by Tobin's q can emerge due to the coexistence of low cash flow state and low price of capital goods, which is translated into good investment opportunities (Rampini & Viswanathan 2010), a positive shock on adjustment technology followed by a negative shock on output, and an adverse transitory shock to the cash flow with the prospect of future profitability staying robust (Decamps, Gryglewicz, Morellec & Villeneuve 2016). The small magnitude of ϕ_{Qcf} would mitigate the upward bias in the estimated cash flow coefficient and the negative ϕ_{Qcf} would induce a downward bias on the estimated cash flow coefficient. The negative or non-significant covariance between q and cash flow in recent years therefore accounts for the low values of cash flow sensitivity estimated in late periods.

Furthermore, the covariance structures also help to explain the perceived differential cash flow sensitivity between constrained and unconstrained subsamples of firms classified using an indirect proxy for constraints. The widely used constraint measures are WW-index (Whited & Wu 2006), KZ-index (Lamont et al. 2001), HP-index (Hadlock & Pierce 2010), bond-ratings and dividend ratios. The estimated cash flow sensitivity for the constrained firms tends to display lower ("wrong-way") values, which casts doubt on the ability of investment-cash flow sensitivity to capture the firms' financial status (see Kaplan & Zingales 1997, Erickson & Whited 2000, Hadlock & Pierce 2010). However, we discover that constrained firms that have high WW-index, KZ-index, HP-index and no bond-ratings have a negative or a lower ϕ_{Qcf}, which is associated with downward biased estimates of cash flow coefficient. As cash flow coefficients are underestimated for constrained subsamples of firms, they may explain the reversed relationship between the observed investment-cash flow sensitivity and the magnitude of financial constraints. Therefore, our analysis re-examines the argument that a low estimated investment-cash flow sensitivity for constrained firms represents its incapacity to measure the degree of financial constraints.

It is worth noting that although the measurement error in q plays a significant role in shaping the time-series and the cross-section of cash flow sensitivity; we would not postulate that this effect alone can fully account for the observed patterns of cash flow sensitivity. In this chapter, we provide explore one channel, the variance-covariance structure between cash flow and q, but other factors such as capital and labor market frictions are also deemed important in explaining the patterns of cash flow sensitivity.

In order to tackle the issue of measurement error, EW (2000, 2002) have suggested using a high-order moment-based GMM estimator (EW estimator). We show that EW estimator generates a bias in the coefficient of mismeasured variables (attenuation bias) if the assumptions adopted in the classical errors-in-variables model do not hold. The attenuation bias from the mismeaured variable still affects the coefficients on the other variables via the covariance-variance channel. We design a Monte Carlo experiment in which the classical assumptions are relaxed. In particular, we test the performance of OLS estimator and EW estimator when the error is non-classical, i.e., when the true latent variable is correlated with the measurement error. The simulation under the non-classical error allows the measurement error in the empirical proxy to correlate with the true variable and it results in biased estimates even for the EW estimator. It shows that even though EW estimator can handle the errors-in-variables under the classical assumption, it produces biases in the presence of a non-classical error. Again, the bias in q coefficient produces a downward biased estimate for cash flow sensitivity when there is a negative correlation between q and cash flow under the non-classical assumption as well.

This chapter fits into two strands of literatures in corporate finance and economics. First, it is related to works which attempt to examine the cross-sectional and time-series patterns of cash flow sensitivity (Ağca & Mozumdar 2017, Chen & Chen 2012, Hadlock & Pierce 2010, among many others). This chapter, however, provides an alternative perspective by examining the pattern of covariance between cash flow and q. In particular, we find that the negative or the small positive covariance between

q and cash flow contributes to the low cash flow sensitivity estimated in the late periods and in the constrained samples of firms. To our best knowledge, this is the first paper to employ evidence from the covariance between q and cash flow to explain the patterns of cash flow sensitivity. Second, it adds to the studies concerning the impact of measurement error in variables. Prior literature has examined a number of ways to deal with measurement error.[1] The most widely used one is EW estimator. Notably, EW (2000, 2002) assert that cash flow sensitivity should disappear once EW estimator is applied to address the measurement-error bias. It falls short, however, as it relies on the classical assumption of measurement error. We show that the attenuation bias is still present and inflicts the estimated coefficients on cash flow when the error is non-classical. In this sense, this chapter is linked to literature that examines the consequences of non-classical measurement error (e.g., O'Neill & Sweetman 2013, Gottschalk & Huynh 2010).

The remainder of the chapter is structured as follows. Section 4.2 introduces the theory of classical and non-classical measurement error. Section 4.3 describes data source, data variables and present some summary statistics. Section 4.4 presents the time-series regression analysis. Section 4.5 outlines the cross-sectional regression output. Section 4.6 conducts Monte Carlo simulation experiments and discusses the impact of measurement error in the presence of a non-classical error. Section 4.7 makes conclusions.

[1] EW (2000, 2002) have suggested applying the high-order moment-based GMM estimator (EW estimator) to purge the measurement error. Almeida et al. (2010) maintain that EW estimator performs badly in case of heterogeneity and low skewness of data and recommend using instrumental variables-type estimator (see also Ağca & Mozumdar 2017). EW (2012), in response, argue that the poor performance is due to the misuse of starting values and EW estimator outperforms IV estimator when measurement error is serially correlated.

4.2 The theory of measurement error

4.2.1 Classical measurement error theory

According to EW (2000), positive cash flow coefficients can arise from the measurement error in empirical average q. The EW (2000) measurement-error-corrected estimates, which are attained by minimizing the high-order moment equations, are sensitive to the change of starting values (Erickson & Whited 2012) and can only be recovered when the data displays high degree of skewness (Almeida et al. 2010). In this section, we decide to review the impact of measurement error by resorting to the classical measurement error theory. We follow EW (2000) and use their notation to present the cross-sectional estimates. According to the q-investment theory, investment-to-capital ratio is explained by investment opportunities, which is defined as marginal q. The empirical equation with true marginal q is

$$y_i = \chi_i \beta + \mathbf{z}_i \mathbf{B} + u_i, \tag{4.2.1}$$

where y_i is a scalar representing investment scaled by book value of capital, χ_i is the unobservable true marginal q. $\mathbf{z}_i = (c_i \; 1 ...)$ is a $1 \times K$ row vector for perfectly-measured variables which contain cash flow variable c_i, 1 for constant term and other relevant control variables. $\mathbf{B} = (\alpha \; \gamma_0 ...)'$ is a $K \times 1$ vector where the first element , denoted by α, is the coefficient on cash flow. Marginal q is not observed, hence empirically one uses average q to measure marginal q. The observable empirical q is measured as

$$x_i = \chi_i + e_i, \tag{4.2.2}$$

where e_i is the measurement error. Classical measurement error theory assumes that i) u_i is a regression error independent of (χ_i, x_i); ii) e_i is a mean zero error independent of $(\chi_i, \mathbf{z}_i, u_i)$; iii) (u_i, e_i, χ_i, x_i) are independent and identically distributed (i.i.d). Substituting (4.2.2) into (4.2.1), one can obtain

$$y_i = x_i\beta + \mathbf{z}_i\mathbf{B} + (u_i - e_i\beta), \tag{4.2.3}$$

where the error term in the new regression $(u_i - e_i\beta)$ is correlated with x_i since $\mathrm{Cov}(e_i, x_i) \neq 0$. Hence orthogonality condition fails to stand and it results in inconsistent estimation for the coefficients in x_i and $\mathbf{z}_i$. As in EW (2000), we partial out the effect of perfectly-measured variables $\mathbf{z}_i$.[2] For simplicity, we drop the script i. One can rewrite the expression Eqn (4.2.1) and Eqn (4.2.2) in terms of population residuals:

$$\dot{y} = \dot{\chi}\beta + u, \tag{4.2.4}$$

$$\dot{x} = \dot{\chi} + e. \tag{4.2.5}$$

$(\dot{y}, \dot{x}, \dot{\chi})$ are the residuals of regressing (y, x, χ) on $\mathbf{z}$. The probability limit of the OLS coefficient on the mismeasured variable is[3]

$$\mathrm{plim}(\hat{\beta}_{OLS}) = \beta\frac{1}{1 + \frac{\mathrm{Var}(e)}{\mathrm{Var}(\chi|\mathbf{z})}}, \tag{4.2.6}$$

where $\mathrm{Var}(\chi|\mathbf{z}) \equiv \mathrm{Var}(\dot{\chi})$ is the error variance from regressing χ on $\mathbf{z}$. Denote $\lambda = \frac{1}{1+\mathrm{Var}(e)/\mathrm{Var}(\chi|\mathbf{z})}$ as the measure of the reliability of the data. $\lambda = 1$ if $\mathrm{Var}(e) = 0$ and λ reflects the measurement quality of the empirical q variable. Since $0 < \lambda < 1$, $\hat{\beta}_1$ is always biased downward. The bias is called attenuation bias. Higher measurement error variance relative to the error variance $(\mathrm{Var}(e)/\mathrm{Var}(\chi|\mathbf{z}))$ results in higher attenuation bias in q coefficient.

Denote ϕ_{yc} (ϕ_{xc}) as the coefficient on c in a linear projection of y (x) on $\mathbf{z}$. Assume

[2]Applying Frisch-Waugh-Lovell (FWL) theorem, one can partial out the perfectly-measured variables. Define $(\phi_{y\mathbf{z}}, \phi_{x\mathbf{z}}, \phi_{\chi\mathbf{z}}) = [E(\mathbf{z}_i^{'}\mathbf{z}_i)]^{-1}E(\mathbf{z}_i^{'}(y_i, x_i, \chi_i))$. Multiplying Eqn (4.2.1), Eqn (4.2.2) by $\mathbf{z}_i^{'}$, taking expectation and then multiplying by $[E(\mathbf{z}_i^{'}\mathbf{z}_i)]^{-1}$, Eqn (4.2.1), Eqn (4.2.2) become $\phi_{y\mathbf{z}} = \phi_{\chi\mathbf{z}}\beta + \mathbf{B}, \phi_{x\mathbf{z}} = \phi_{\chi x}$. Multiplying by $\mathbf{z}_i$, we have $\mathbf{z}_i\phi_{y\mathbf{z}} = \mathbf{z}_i\phi_{\chi\mathbf{z}}\beta + \mathbf{z}_i\mathbf{B}, \mathbf{z}_i\phi_{x\mathbf{z}} = \mathbf{z}_i\phi_{\chi\mathbf{z}}$. Subtracting from Eqn (4.2.1), Eqn (4.2.2) yields $\dot{y}_i = \dot{\chi}_i\beta + u_i, \dot{x}_i = \dot{\chi}_i + e_i$ where $(\dot{y}_i, \dot{x}_i, \dot{\chi}_i)$ are population residuals of regressing (y_i, x_i, χ_i) on $\mathbf{z}_i$.

[3]As $\hat{\beta}_{OLS} = \frac{\mathrm{Cov}(\dot{x},\dot{y})}{\mathrm{Var}(\dot{x})} = \frac{\mathrm{Cov}(\dot{\chi}+e,\dot{\chi}\beta+u)}{\mathrm{Var}(\dot{\chi}+e)}$, $\mathrm{plim}(\hat{\beta}_{OLS}) = \frac{\beta\mathrm{Var}(\dot{\chi})}{\mathrm{Var}(\dot{\chi})+\mathrm{Var}(e)}$.

that x and c are our main regressors in the bivariate regression. The probability limit of the cash flow coefficient is [4]

$$\text{plim}(\hat{\alpha}_{OLS}) = \phi_{yc} - \phi_{xc}\text{plim}(\hat{\beta}_{OLS}). \tag{4.2.7}$$

$\alpha = \phi_{yc} - \phi_{\chi c}\beta$ if no variable is mismeasured. $\phi_{\chi c} = \phi_{xc}$ as e is independent of c. One can write

$$\text{plim}(\hat{\alpha}_{OLS}) - \alpha = -\phi_{xc}(\text{plim}(\hat{\beta}_{OLS}) - \beta). \tag{4.2.8}$$

We have shown in (4.2.7) that measurement error always biases the OLS estimate of β downward. However, the direction in which measurement error biases the estimate of cash flow coefficient will depend on ϕ_{xc}, which is the linear coefficient of regressing x on c after controlling for all other variables in $\mathbf{z}$ or, the covariance between x and c scaled by variance of c, denoted as $\frac{\text{Cov}(x,c)}{\text{Var}(c)}$, in the bivariate regression. (For simplicity, we now focus on the bivariate regression case.) If x and c are positively correlated (ϕ_{xc} is positive), the effect of measurement error will bias the OLS estimate of β downward and then α upward. That is exactly how measurement error leads to a positive coefficient on cash flow while it should be zero in the frictionless world by theory. However, if x and c are *negatively* correlated, which means $\phi_{xc} < 0$, then measurement error will bias both the estimates of β and α *downward*.

The negative correlation between cash flow and investment opportunities as proxied by Tobin's q can emerge for several reasons: First, as mentioned in Rampini & Viswanathan (2010), economic downturn indicates low cash flow state, but it also leads to low price of capital and thus good investment opportunities. This creates a scenario in which cash flow and investment opportunities are negatively correlated. Second, marginal q is not only informative about the shocks to productivity, it also captures the shocks to adjustment technology (see Papanikolaou 2011, Belo et al. 2014, among others). A positive shock on adjustment technology, which lowers investment frictions and improves investment opportunities, accompanied by a negative shock on

[4]This is the result of partialling out cash flow variable (see footnote 2).

output can lead to a negative relationship between marginal q and cash flow. Third, Decamps, Gryglewicz, Morellec & Villeneuve (2016) argue that cash flow is subject to both permanent shocks and transitory shocks. While the former not only affect a firm's immediate productivity, but also change the long-run aspects of the firm's profitability and thereby investment opportunities. The transitory shocks, however, only influence the firm's short-run cash flow and are uninformative about the firm's future productivity (see also Chang et al. 2014, Gryglewicz et al. 2017, among others). When the transitory shocks exhibit negative correlation with the permanent shocks, one should observe a negative correlation between cash flow and investment opportunities. For instance, if the firms face an adverse shock in the consumer preferences while at the same time receive a cash windfall (e.g., a won lawsuit, an acceleration in customer payment), cash flows will vary negatively with the future growth opportunities.

4.2.2 Non-classical measurement error theory

High-order moment-based GMM estimator by Erickson & Whited (2000) (EW estimator) has been criticized due to the distributional assumption imposed on the data, in which marginal q variable must display high degrees of skewness. Most of all, EW (2000) rely on the classical assumptions of measurement error theory in order to derive high-order moment-based GMM estimator. With a classical measurement error, EW estimator can provide consistent estimates but it performs poorly if measurement error is non-classical. Although EW (2000) provide economic reasonale for the zero independence between regression error u and explanatory variables, some of the other assumptions may not necessarily hold.

The measurement error can be non-classical in the sense that the error is correlated with the latent true q variable, that is, $\mathrm{E}(\chi e) \neq 0$. According to Hayashi (1982), measurement error may arise in the presence of market power or decreasing returns-to-scale in the production function, which makes average q depart from marginal q. The divergence between average q and marginal q equals a fraction of expected discounted revenue stream, scaled by capital. As marginal q represents the expected discounted value of future marginal net profit from investing one extra unit of capital, positive correlation between marginal q and measurement error may exist. Also, we expect that a positive relationship between cash flow and measurement error may be present. On the other hand, average q understates marginal q by ignoring the collateral effect of investment as installed capital can relax the borrowing constraints (Hennessy 2004, Hennessy, Levy & Whited 2007). The collateral value of investment represents another source of measurement error. The collateral value of investment changes with the amount of capital investment, therefore one should expect it to change with marginal q as well since the optimality condition equates marginal q with marginal cost of investment.

Now we turn to Eqn (4.2.4) and Eqn (4.2.5) but remove the assumption that e is uncorrelated to χ. The probability limit of the OLS estimate on q coefficient under $E(\chi e) \neq 0$ is thereby[5]

$$\text{plim}(\hat{\beta}_{OLS}) = \beta \frac{1}{1 + \frac{\text{Var}(e)+\text{Cov}(e,\chi|\mathbf{z})}{\text{Var}(\chi|\mathbf{z})+\text{Cov}(e,\chi|\mathbf{z})}}. \tag{4.2.9}$$

$\text{Cov}(e, \chi|\mathbf{z})$ denotes the covariance between measurement error and latent true q after partialling out the effect of $\mathbf{z}$. Downward bias will be aggravated when $\text{Cov}(e, \chi|\mathbf{z}) > 0$. Again, the downward bias brought by $\hat{\beta}_{OLS}$ will spill over and push the OLS estimates of α downward via the negative ϕ_{xc}.

Next, we investigate the impact of non-classical measurement error on EW estimator. We focus on the third-order-product moment condition in Erickson & Whited (2000, 2002) by expressing $(\dot{y}, \dot{x})$ in terms of β and moments of $(u, e, \dot{\chi})$:

$$E(\dot{y}^2\dot{x}) = \beta^2\text{E}(\dot{\chi}^3) + \beta^2\text{E}(\dot{\chi}^2 e), \qquad E(\dot{y}\dot{x}^2) = \beta\text{E}(\dot{\chi}^3) + \beta\text{E}(\dot{\chi}e^2) + 2\beta\text{E}(\dot{\chi}^2 e).$$

The third-order moment-based estimator (GMM3) for β shown in EW (2000) is

[5] $\beta_{OLS} = \frac{\text{Cov}(\dot{x},\dot{y})}{\text{Var}(\dot{x})} = \frac{\text{Cov}(\dot{\chi}+e,\beta\dot{\chi}+u)}{\text{Var}(\dot{\chi}+e)} = \frac{\beta[\text{Var}(\dot{\chi})+\text{Cov}(e,\dot{\chi})]}{\text{Var}(\dot{\chi})+2\text{Cov}(e,\dot{\chi})+\text{Var}(e)}$ and $\text{Cov}(e, \dot{\chi}) \equiv \text{Cov}(e, \chi|\mathbf{z})$.

$\frac{E(\dot{y}^2\dot{x})}{E(\dot{y}\dot{x}^2)}$ under the identifying assumptions that $\beta \neq 0$ and $E(\dot{\chi}^3) \neq 0$ and, also the classical assumptions that $\mathrm{E}(\dot{\chi}^2 e) = 0$ and $\mathrm{E}(\dot{\chi}e^2) = 0$. However, it is clear that by dividing one can not recover GMM3 estimator if the independence requirement between measurement error and true q, i.e. $\mathrm{E}(\dot{\chi}^2 e) = 0$, $\mathrm{E}(\dot{\chi}e^2) = 0$, is relaxed. More specifically,

$$\mathrm{plim}(\hat{\beta}_{GMM3}) = \frac{E(\dot{y}^2\dot{x})}{\mathrm{E}(\dot{y}\dot{x}^2)} = \beta\big(1 - \frac{\mathrm{E}(\dot{\chi}^2 e) + \mathrm{E}(\dot{\chi}e^2)}{E(\dot{\chi}^3) + E(\dot{\chi}e^2) + 2E(\dot{\chi}^2 e)}\big).$$

The above expression equals β when $\mathrm{E}(\dot{\chi}^2 e) = \mathrm{E}(\dot{\chi}e^2) = 0$. The bias arises from the dependence between $\dot{\chi}$ and e and the bias is more pronounced if $E(\dot{\chi}^3)$ is low, meaning that marginal q is not highly skewed. The estimator will exert a downward bias on $\hat{\beta}$ when the moments of measurement error and marginal q are positive. The bias on the estimate of α is also pronounced for higher-order moment estimator. The probability limit of coefficient on cash flow variable is

$$\mathrm{plim}(\hat{\alpha}_{GMM3}) = \phi_{yc} - \phi_{xc}\mathrm{plim}(\hat{\beta}_{GMM3}).$$

Again, the bias on the q coefficient estimates will spill over and affect the estimates on cash flow coefficient when $\phi_{xc} \neq 0$. Almeida, Campello & Galvao (2010) argue that instrumental-variables-type estimator (IV estimator) using lagged mismeasured regressor as instruments performs better than EW estimator. However, as shown in Erickson & Whited (2012), it also produces bias on the estimates of q coefficient and then on cash flow coefficient if the measurement error is serially correlated. As in Almeida, Campello & Galvao (2010), one needs to take first difference to the equations Eqn (4.2.4) and Eqn (4.2.5) to eliminate individual effects. Using twice lagged value of empirical q ($\dot{x}_{it-2}$) as instrumental variable, the IV estimator for β is $\beta = \frac{\mathrm{Cov}(\dot{x}_{it-2}, \Delta\dot{y}_{it})}{\mathrm{Cov}(\dot{x}_{it-2}, \Delta\dot{x}_{it})}$. The probability limit of IV estimator for β is $\mathrm{plim}(\beta) = \frac{\beta \mathrm{Cov}(\dot{x}_{it-2}, \Delta\dot{\chi}_{it})}{\mathrm{Cov}(\dot{x}_{it-2}, \Delta\dot{\chi}_{it}) + \mathrm{Cov}(\dot{x}_{it-2}, \Delta e_{it})}$. $\mathrm{Cov}(\dot{x}_{it-2}, \Delta e_{it}) \neq 0$ if e_{it} is serially correlated. If both $\mathrm{Cov}(\dot{x}_{it-2}, \Delta e_{it})$ and $\mathrm{Cov}(\dot{x}_{it-2}, \Delta\dot{\chi}_{it})$ are negative, IV estimator may underestimate β.

4.3 Data and summary statistics

The sample is extracted from the Compustat industry annual file, covering all manufacturing firms (SIC between 2000 and 3999) incorporated in the U.S. between 1970 and 2016. Inside the parenthesis, we write the data name in the Compustat industry annual file. Investment is measured as capital expenditure ($capx$) on an annual basis. Net capital is defined as net property, plant and equipment ($ppent$). Cash flow is income before extraordinary items (ib) plus depreciation and amortization (dp). Change in cash holdings is the change of cash and short-term investments (che). The growth opportunities is proxied by Tobin's q, which is the market value divided by the book value. Market-to-book of asset ratio (denoted by MB) is defined as the market value of assets (the market value of assets is market value of common stock ($prcc\_f \times csho$) plus total assets (at) minus total common equity (ceq) minus deferred taxes ($txdb$)) divided by total value of book assets (at). The disadvantage of this widely-used measure is that it reflects the growth opportunities for all assets rather than just capital stock (Erickson & Whited 2012). Hence, we also measure Tobin's q as market-to-book ratio of capital stock (denoted by q^K) since it leads to less measurement-error biases relative to market-to-book of assets ratio. We adopt the construction of q^K in Chen & Chen (2012), market value of capital is computed as market value of assets (the sum of market value of common stock, total liability (lt), and preferred stock ($pstk$) minus deferred taxes ($txditc$), less the difference between book value of assets (at) and book value of capital ($ppent$). By this design, we remove the value of current asset as well as all other asset such as intangible asset which do not account for the market value of capital stock. It eliminates the concern that Tobin's q may capture more than the contribution of capital stock if unquantifiable asset value is included in the numerator.[6] We use the market-to-book ratio at the beginning of the period since managers make investment decisions upon observing investment opportunities at the start of the year. According to the q theory, both capital expenditure and cash flow are deflated by

[6]EW (2012) report that placing the sum of debt and equity less current assets as numerator will create room for a bias if total assets consist of more than capital stock and current assets.

capital stock (Hayashi & Inoue 1991). Following Almeida et al. (2004), we also delete the firms that have sales or asset growth exceeding 100% to eliminate the effect of business discontinuities. We drop the observations with assets, sales or capital stock less than 1 million USD to eliminate the effect of outliers. We winsorize all relevant variables at 1% in each year.

Table 4.1 provides summary statistics, serial correlations and cross-variable correlations for the regression variables. We divide the full sample into two periods: earlier period 1970-1990 and recent period 1991-2016. We report the results for q variable measured by both market-to-book of capital (q^K) and market-to-book of asset (MB) ratio. It shows that cash flow and Tobin's q have high volatility in the late decades. Also another three salient features are present: First, q variable, measured by q^K or MB, has displayed a high degree of skewness, which is an important assumption underlining EW estimator (EW estimator is formed with the non-zero third-order moment being the denominator). Second, q^K is highly autocorrelated in both early periods and recent periods, which may undermine the use of instrumental-variables-type estimators (Almeida et al. 2010). Third, q variables are negatively correlated with cash flow variables in the recent decades, which lays foundations for our explanation of investment-cash flow sensitivity via the variance-covariance structure between cash flow and q.

4.4 Estimations across time

4.4.1 The time-series pattern of cash flow sensitivities

We divide the full sample into 9 five-year subsample periods. Inv. is defined as the firm's capital expenditure. ΔCash is defined as the change of firm's cash and short-term securities. CF is firm's income before extraordinary items plus depreciation. Then, we perform a regression of investment on beginning-of-year Tobin's q (denoted as Q) and cash flow with firm-specific and year fixed effects. For each five-year period,

Table 4.1: Summary statistics

This table displays summary statistics for the main regressor variables. The firm-level data is collected for all manufacturing firms (SIC code between 2000 and 3999) in U.S. from Compustat, covering 1970-2016 period. The full sample is divided into two periods: 1970-1990 and 1991-2016. For each of the variable, it reports mean, standard deviation, skewness, kurtosis, first-order serial correlation and the correlation across the variables. All variables that are normalized by K (AT) are divided by beginning-of-period net property, plant and equipment (total book value of assets). Inv. is defined as the firm's capital expenditure. ΔCash is defined as the change of firm's cash and short-term securities. CF is firm's income before extraordinary items plus depreciation. q^K is beginning-of-period Tobin's q measured by market value of capital scaled by net property, plant and equipment. MB is beginning-of-period Tobin's q measured by market value of asset scaled by book value of asset.

Sample period: 1970-1990	Mean	Std. Dev.	Skew.	Kurt.	Serial Corr.	Cross-variable Corr.				
						Inv./K	ΔCash/AT	q^K	MB	CF/K
Inv./K	0.256	0.206	2.236	9.847	0.412	1.000				
ΔCash/AT	0.009	0.071	1.220	11.318	-0.125	-0.041	1.000			
q^K	2.183	3.545	3.792	22.264	0.803	0.295	0.052	1.000		
MB	1.283	0.782	3.225	17.822	0.831	0.259	0.058	0.886	1.000	
CF/K	0.344	0.446	-0.521	12.848	0.691	0.338	0.182	0.273	0.202	1.000

Sample period: 1991-2016	Mean	Std. Dev.	Skew.	Kurt.	Serial Corr.	Cross-variable Corr.				
						Inv./K	ΔCash/AT	q^K	MB	CF/K
Inv./K	0.246	0.230	2.378	10.179	0.487	1.000				
ΔCash/AT	0.008	0.111	0.852	8.780	-0.063	0.008	1.000			
q^K	7.809	16.326	5.446	44.672	0.366	0.366	0.054	1.000		
MB	1.828	1.279	2.638	12.156	0.487	0.287	0.104	0.676	1.000	
CF/K	0.082	2.037	-4.263	35.608	0.487	0.051	0.174	-0.207	-0.079	1.000

the OLS regression is run:

$$\text{Inv./K}_{it} = \gamma_0 + \beta Q_{it-1} + \alpha \text{CF/K}_{it} + \epsilon_{it}, \tag{4.4.1}$$

where α (β) is the cash flow (q) sensitivity of investment. In this subsample-period regression, Q_{it-1} is beginning-of-year Tobin's q measured by market-to-book of capital ratio (q^K). With regard to the cash flow sensitivity of cash, we follow Almeida, Campello & Weisbach (2004) and perform the following regression:

$$\Delta\text{Cash/AT}_{it} = \gamma_0 + \beta Q_{it-1} + \alpha \text{CF/AT}_{it} + \gamma_1 \text{Size}_{it} + \epsilon_{it}, \tag{4.4.2}$$

where α (β) is the cash flow (q) sensitivity of cash. The change in cash holdings and cash flow are deflated by total assets, Q_{it-1} is beginning-of-year Tobin's q measured by market-to-book of asset ratio (MB) and Size_{it} is the natural log of total assets.

Table 4.2: Cash flow sensitivity of investment and cash across periods

The top panel reports the coefficient estimates of investment on cash flow and Tobin's q, measured by market-to-book of capital ratio (q^K) based on Eqn 4.4.1:

$$\text{Inv./K}_{it} = \gamma_0 + \beta Q_{it-1} + \alpha \text{CF/K}_{it} + \epsilon_{it}.$$

The bottom panel reports the the coefficient estimates of cash on cash flow and Tobin's q, measured by market-to-book of asset ratio (MB) based on Eqn 4.4.2:

$$\Delta\text{Cash/AT}_{it} = \gamma_0 + \beta Q_{it-1} + \alpha \text{CF/AT}_{it} + \gamma_1 \text{Size}_{it} + \epsilon_{it}.$$

s.e. standards for robust standard error. Firm fixed effect and year fixed effect are included in all of the OLS regression. GMM3 (GMM5) denotes the EW estimator which utilizes third(fifth)-order information of the regression variables. The data variables are within-transformed to remove the firm fixed effect when applying GMM estimator. The table also reports the J statistics along with their p-values for GMM5 estimator to test the overidentifying conditions. ***, **, *indicate significance at the 1%, 5% and 10% levels.

Period	OLS estimator				GMM3 estimator				GMM5 estimator					
Dependent Variable	Independent Variables													
Inv./K	Q	s.e.	CF/K	SE	Q	s.e.	CF/K	s.e.	Q	s.e.	CF/K	s.e.	J stats.	p-value
1972-1977	0.010***	0.002	0.270***	0.020	0.048	0.046	0.126***	0.065	0.026***	0.004	0.144***	0.018	2.655	0.753
1978-1981	0.021***	0.004	0.267***	0.020	0.114	0.084	0.061	0.079	0.071***	0.011	0.090***	0.029	3.822	0.575
1982-1986	0.023***	0.003	0.131***	0.015	0.055	0.049	0.022	0.057	0.068***	0.004	0.007	0.022	5.583	0.349
1987-1991	0.016***	0.002	0.058***	0.009	0.034	0.052	0.029	0.054	0.032***	0.003	0.050***	0.010	16.738	0.005
1992-1996	0.010***	0.001	0.048***	0.008	0.018	0.030	0.057	0.032	0.025***	0.002	0.022***	0.008	13.028	0.023
1997-2001	0.007***	0.001	0.022***	0.006	0.013	0.029	0.014	0.023	0.016***	0.001	0.020***	0.005	24.085	0.000
2002-2006	0.006***	0.001	0.005	0.005	0.010	0.023	0.007	0.018	0.010***	0.001	0.010***	0.004	33.260	0.000
2007-2011	0.007***	0.001	0.000	0.004	0.008	0.018	0.011	0.026***	0.011***	0.001	0.005	0.003	27.054	0.000
2012-2016	0.004***	0.001	-0.002	0.004	0.008	0.024	0.012	0.018	0.006***	0.001	0.006**	0.003	9.306	0.097
Period	OLS estimator				GMM3 estimator				GMM5 estimator					
Dependent Variable	Independent Variables													
ΔCash/K	Q	s.e.	CF/K	s.e.	Q	s.e.	CF/K	s.e.	Q	s.e.	CF/K	s.e.	J stats.	p-value
1972-1977	-0.017***	0.002	0.224***	0.023	-0.082	0.068	0.459	0.257	-0.058***	0.007	0.369***	0.035	29.727	0.000
1978-1981	-0.003	0.005	0.224***	0.026	0.899	1.233	-1.301	2.066	-0.066***	0.016	0.318***	0.031	22.356	0.000
1982-1986	-0.011	0.006	0.211***	0.027	1.197	1.154	-1.948	2.080	-0.080***	0.013	0.339***	0.032	48.339	0.000
1987-1991	0.008	0.006	0.149***	0.027	-0.567	0.988	0.786	1.112	0.131***	0.020	0.018	0.033	15.338	0.009
1992-1996	0.000	0.004	0.168***	0.026	0.329	0.204	-0.344	0.317	0.092***	0.013	0.019	0.029	26.850	0.000
1997-2001	0.003	0.003	0.116***	0.026	0.156***	0.045	-0.033	0.056	0.087***	0.007	0.045**	0.021	22.747	0.000
2002-2006	0.003	0.004	0.161***	0.035	0.127***	0.039	0.021	0.055	0.102***	0.009	0.054**	0.024	23.670	0.000
2007-2011	-0.002	0.005	0.116***	0.035	0.475	0.627	-0.406	0.714	0.119***	0.018	0.002	0.031	16.095	0.007
2012-2016	0.003	0.005	0.028	0.044	-0.509	0.963	0.854	1.482	0.107***	0.018	-0.085**	0.043	18.087	0.003

The top panel of Table 4.2 reports the coefficient estimates of investment on cash flow and Tobin's q measured by market-to-book of capital ratio (q^K). The bottom panel reports the the coefficient estimates of cash on cash flow and market-to-book of asset ratio (MB). We apply OLS estimator as well as EW's (2000, 2002) high-order moment-based GMM estimator (EW estimator), which are intended to address the measurement error in q under the classical assumption. GMM3 (GMM5) denotes EW estimator which uses information of moments up to 3 (5).[7] The appeal of using overidentified estimator (GMM5 estimator) is that it can provide the J-test of overidentifying conditions, which can be used to examine departures from the classical assumptions of EW estimators. We employ both GMM3 and GMM5 estimators as the results based on GMM5 estimator are sensitive to the change of starting values (EW, 2012).[8] Within-transformation is usually applied to remove the individual fixed effect. Nonetheless, Lewellen & Lewellen (2016) are reluctant to demean variables as it requires firms to have multiple observations and hence induces biases on the slope estimates. Also EW (2012) suggest that EW estimator produces significant biases if within-transformation is applied to eliminate the firm fixed effect. Therefore, we report results for data both in the within-transformation form and in the level form as in EW (2012). The OLS estimates of investment-cash flow sensitivity decrease over time and similar pattern is shown for the GMM estimates albeit less pronounced, consistent with what Chen & Chen (2012) have documented. For instance, OLS estimate of α equals 0.27 and is statistically significant in 1972-1976. Afterwards, it decreases and disappears, becoming statistically insignificant in the recent years. The GMM5 estimator of investment-cash flow sensitivity stands the J-test of overidentifying restrictions in the early years at 5% significance level but it fails in the recent years.[9] The decreasing pattern can also be observed for the OLS estimates and GMM5 estimates of cash-cash

[7]Please refer to Section 2 for details of GMM3 estimtor and Appendix 4.B for details regarding GMM4 or GMM5 (higher-order moment-based estimator).

[8]The starting value we use are OLS estimates, GMM3 estimates and 0.1 to 0.5 with an increment of 0.1

[9]Note that the failure in J-test of overidentifying restrictions indicates that one of the classical assumptions is violated

flow sensitivity. OLS coefficients for cash flow sensitivity of cash decline but they still remain significant in the late periods. GMM3 estimates of cash-cash flow sensitivity are negative in 5 out of 9 periods, in line with the argument of negative propensity to save (Riddick & Whited 2009), while GMM5 estimator only shows negative cash-cash flow sensitivity in 2012-2016. All of the tests of overidentifying restrictions for GMM5 estimator of cash-cash flow sensitivity fail. The OLS and GMM3 estimates on Q are mostly insignificant, which echoes the argument in Almeida et al. (2004) that Q is less important in the cash-cash flow regression. Almeida et al. (2004) point out that cash-cash flow regression places financial variable as opposed to real variable on the left hand side and the measurement error in q has is less of a concern. Hence, most of the measurement-error-in-q literature focus on the study of investment-cash flow sensitivity.[10]. We thereafter use investment-cash flow sensitivity as a subject to examine the impact of the measurement error.

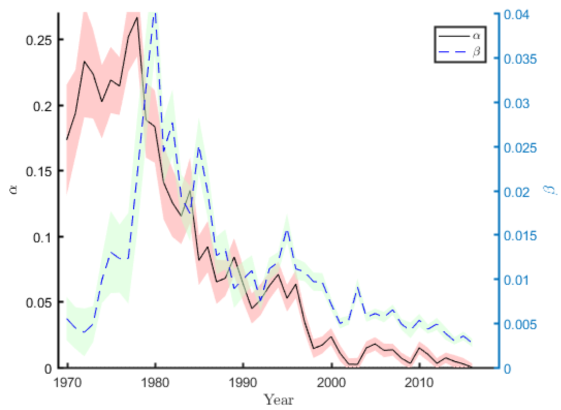
We plot the investment-q sensitivity and investment-cash flow sensitivity for each year in Figure 4.1 and Figure 4.2. In this year-by-year regressions, we also use market-to-book of asset ratio (MB) to proxy for Tobin's q based on Almeida & Campello (2007). The OLS estimates and GMM5 estimates of α (investment-cash flow sensitivity) and β (investment-q sensitivity) are presented by year for both data in the level form and in the within-transformation form in Figure 4.1 (q^K as Tobin's q) and Figure 4.2 (MB as Tobin's q). There are no substantial difference in the regression results between the leveled data and the within-transformed data except that one can observe more negative estimates for α with the within-transformed data in late years. The OLS estimates of cash flow sensitivity have declined gradually over time and eventually became insignificantly different from zero. GMM5 estimates of investment-cash flow sensitivity began to decline from 1980s. After 2000, they became essentially small and statistically insignificant (15 out of 17 estimated cash flow sensitivities from 2000

[10]The examples of contributions that study investment-cash flow sensitivity via the channel of measurement error are Erickson & Whited (2000, 2002, 2012), Gomes (2001), Alti (2003), Cooper & Ejarque (2003), Cummins, Hassett & Oliner (2006), Almeida, Campello & Galvao (2010), Ağca & Mozumdar (2017), among others

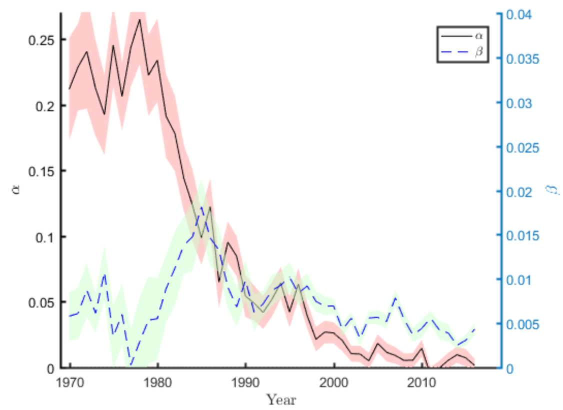
Figure 4.1: Investment-cash flow sensitivity by year (q^K as Tobin's q)

OLS regression

(a) Data in levels

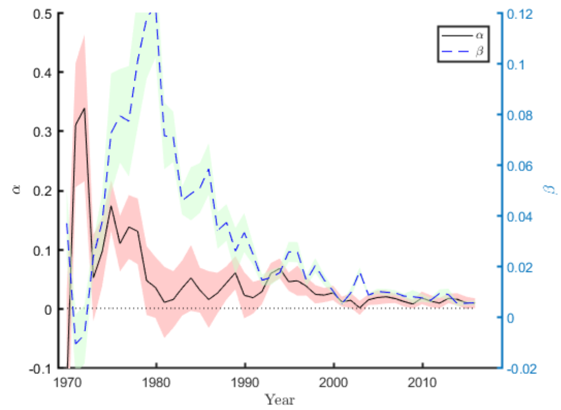


(b) Within-transformed data



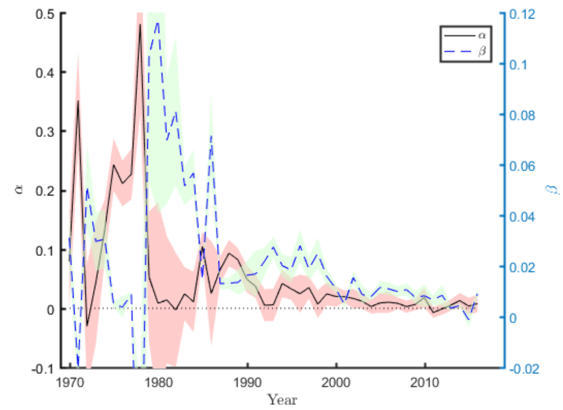
GMM5 estimation

(c) Data in levels



J-statistic: 140.71 (0.000) τ^2: 0.411

(d) Within-transformed data



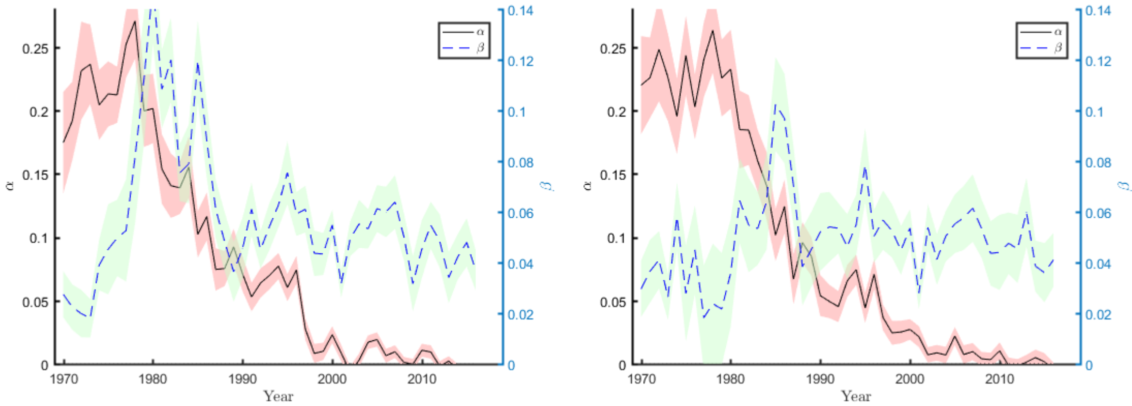
J-statistic: 59.89 (0.000) τ^2: 0.403

Note: Tobin's q is measured as market-to-book ratio of capital stock. The first two graph plots coefficients on cash flow (solid line, plotted against the left axis) and q (long-dashed line, plotted against the right axis) by running OLS regression of investment on q and cash flow. The results are reported for data in levels (a,c) and within-transformed data (b,d). The last two graphs plot coefficients on cash flow (solid line, plotted against the left axis) and q (long-dashed line, plotted against the right axis) estimated with fifth-order moment estimator (GMM5), for data in levels (b) and within-transformed data (d). J-tests of overidentifying restrictions for the panel estimations of 1970-2016 along with their p-values are provided below the graph of GMM5 estimation. τ^2 (reported below the GMM5 graph) is a measure of the proxy quality of q^K. Shaded areas indicate 95% confidence interval.

Figure 4.2: Investment-cash flow sensitivity by year (MB as Tobin's q)

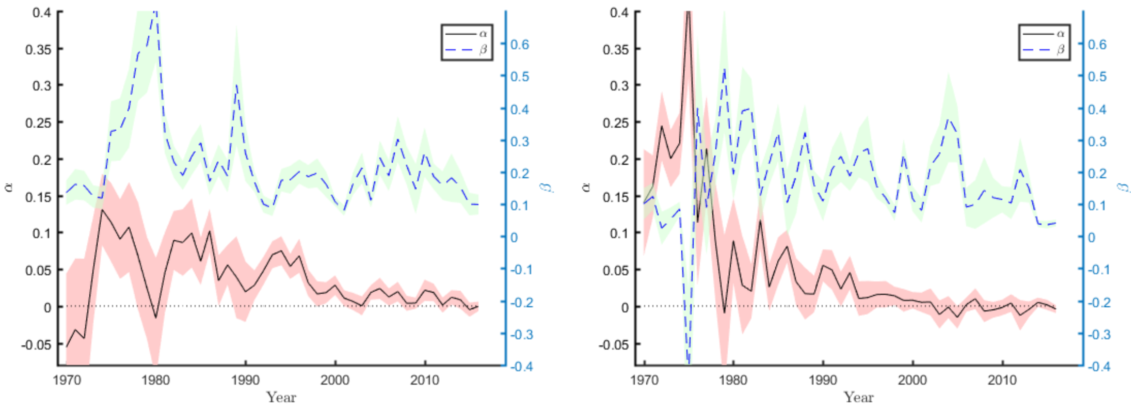
OLS regression

(a) Data in levels (b) Within-transformed data



GMM5 estimation

(c) Data in levels (d) Within-transformed data



J-statistic: 243.74 (0.000) τ^2: 0.217 J-statistic: 64.26 (0.000) τ^2: 0.257

Note: Tobin's q is measured as market-to-book ratio of total assets. The first two graph plots coefficients on cash flow (solid line, plotted against the left axis) and Tobin's q (long-dashed line, plotted against the right axis) by running OLS regression of investment on q and cash flow. The results are reported for data in levels (a,c) and within-transformed data (b,d). The last two graphs plot coefficients on cash flow (solid line, plotted against the left axis) and q (long-dashed line, plotted against the right axis) estimated with fifth-order moment estimator (GMM5), for data in levels (b) and within-transformed data (d). J-tests of overidentifying restrictions for the panel estimations of 1970-2016 along with their p-values are provided below the graph of GMM5 estimation. τ^2 (reported below the GMM5 graph) is a measure of the proxy quality of MB. Shaded areas indicate 95% confidence interval.

to 2016 are insignificant). Panel estimation for observations from 1970 to 2016 with GMM5 estimator is also carried out to test the overidentification restrictions and measurement quality of q. τ^2 is an index for the proxy quality of q. Consistent with EW (2012), it shows that market-to-book ratio of capital stock, rather than total assets, is a better proxy for investment opportunities. The J-statistic is quite large for both the leveled data and the within-transformed data, indicating that one of the EW-estimator assumptions is not satisfied. Overall, cash flow sensitivities of investment estimated by both OLS estimator and EW estimator have shown lower values in the late years than those in the early periods.

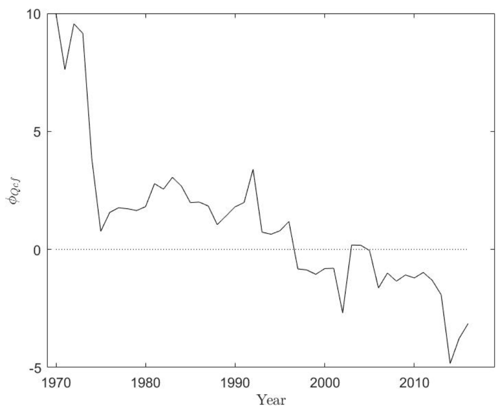
4.4.2 Variance-covariance structure over time

The neoclassical frictionless q-investment theory (Lucas & Prescott (1971) and Mussa (1977)), under which optimality condition equates marginal return of capital (marginal q) with marginal cost of investment, predicts that cash flow should have no explanatory power on investment ($\alpha = 0$). Denote ϕ_{Qcf} as the linear projection of q on cash flow. Note that $\phi_{Qcf} = \frac{\text{Cov}(Q,cf)}{\text{Var}(cf)}$ when only cash flow is included in explaining q. We have shown in Eqn (4.2.8) that the bias afflicting q coefficients will drive the estimates of cash flow sensitivity (α) upward from its theoretical value if there is positive covariance between q and cash flow (i.e., positive ϕ_{Qcf}). One the other hand, it would drive estimated α *downward* from or toward zero if there is *negative* or close-to-zero ϕ_{Qcf}. In order to associate the time-series structure of variance-covariance with the pattern of cash flow sensitivity, we plot ϕ_{Qcf} for each year in Figure 4.3. Again we consider both data in levels and data that are within-transformed. It reveals that ϕ_{Qcf} is highly positive in the early years but decrease significantly over time and toward zero. For the data in levels, one can observe a negative ϕ_{Qcf} in the recent years. For within-transformed data, the negative values are less common but ϕ_{Qcf} still exhibit an extremely small magnitude. Such a pattern explains why the estimated α is low in the recent periods as it is biased downward from (for negative ϕ_{Qcf}) or toward its true value (for small ϕ_{Qcf}). Therefore, we argue that, via the variance-covariance channel,

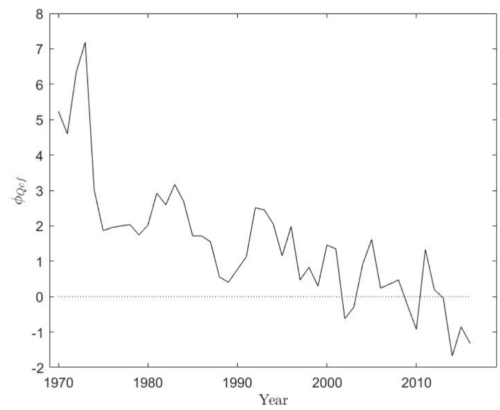
Figure 4.3: Covariance structure of Tobin's q and cash flow by year

Panel A: q^K as Tobin's q

ϕ_{Qcf} for data in levels

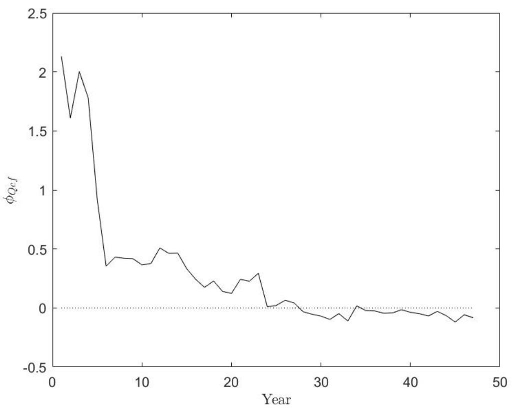


ϕ_{Qcf} for within-transformed data

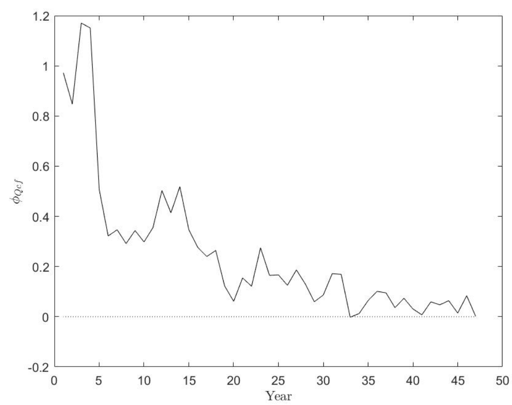


Panel B: MB as Tobin's q

ϕ_{Qcf} for data in levels



ϕ_{Qcf} for within-transformed data



Note: Graph (a) and (b) plot the ϕ_{Qcf} when Q is proxied by market-to-book of capital ratio. Graph (c) and (d) plot the ϕ_{Qcf} when Q is proxied by market-to-book of asset ratio. ϕ_{Qcf} for data in levels is measured as $\frac{\text{Cov}(Q,cf)}{\text{Var}(cf)}$ when both Q and cf are in the level form. ϕ_{Qcf} for within-transformed data is measured as $\frac{\text{Cov}(Q,cf)}{\text{Var}(cf)}$ when both Q and cf are demeaned to remove the individual fixed effect.

measurement error, although inflates the estimates of investment-cash flow sensitivity in the early periods when ϕ_{Qcf} is positive, diminishes the estimates of α in the late periods when ϕ_{Qcf} is negative or small.

4.4.3 The effect of covariance on the time-series pattern

In this section, we aim to quantify the effect of measurement error on the time-series trend of cash flow sensitivity under the classical assumption. We simulate $N = 1000$ individual observations in each simulation and we repeat the procedures 2000 times before the average is taken over the 2000 simulations. The following outlines our data-generating process. We simulate the following variables: y_i, z_i, χ_i, which are assumed to be normally distributed and have the same mean, variance and covariance as investment, cash flow, Tobin's average q respectively from the actual data set. The simulation of the covariance between variables is performed via Cholesky decomposition. Then we pretend that the Tobin's average q, denoted as χ_i, is the true marginal q and artificially add measurement error to the χ_i (See similar methods in Dasgupta et al. 2011).

$$x_i = \chi_i + e_i,$$

where χ_i is regarded as the true q (error-free q) and x_i is the empirical q measured with error (mismeasured q). In line with the classical assumption of measurement error, $e_i \sim N(0, \sigma^2(e))$ is a mean zero error independent of χ_i and z_i. $\frac{\sigma^2(\chi)}{\sigma^2(x)}$ reflects the quality of measurement. One can adjust the variance of e_i to match the measurement quality to the value of around 0.5 as reported in Erickson & Whited (2000), i.e., the variance of e_i is set to be same as the variance of χ_i. After variables of interest are generated, we run the regression of y_i on χ_i (x_i) and z_i.

Table 4.3 presents the OLS regression results with error-free q (χ_i) and mismeasured q (x_i) respectively. It shows that when q variable carries a measurement error, coefficients on q will always be biased downward. However, the direction of bias in cash flow coefficients changes over time. Adding measurement error will bias the cash flow coefficients upward in the early periods from 1977 to 1996 and bias the coefficients on cash flow downward in the late periods from 1997 to 2016. It supports our proposition that measurement error amplifies the cash flow sensitivity in the early years but diminishes the cash flow sensitivity in the recent years, which gives rise to the decreasing trend of cash flow sensitivity. The estimated cash flow sensitivity β_2 declined from 0.2418 in 1977-1981 to 0.0016 in 2012-2016 for the regression with mismeasured q, but the decline is less pronounced, going from 0.2167 to 0.0071, for the regression with error-free q. The time trend for β_2 shows that the declining trend has increased by around 16% from -0.0268 to -0.0318 if error is included in the q.

Table 4.3: Regression with simulated data variables

The table reports estimation results from baseline linear regression with simulated data: $y_i = \beta_0 + \beta_1\chi_i + \beta_2 z_i + \varepsilon$ where y_i, χ_i and z_i are simulated to match the first and second moment observed in the actual data. χ_i is the error-free q. The fourth and fifth column report results from regression model $y_i = \beta_0 + \beta_1 x_i + \beta_2 z_i + \varepsilon$ where x_i is q measured with error. +/- denotes increase/decrease from the estimates using error-free q as regressor. Trend is estimated as regressing the coefficients on the period trend variable, which is 1 in 1977-1981, 2 in 1982-1987 and so forth.

	Error-free q is treated as regressor		Mismeasured q is treated as regressor	
Period	β_1	β_2	β_1	β_2
1977-1981	0.0255	0.2167	0.0118(-)	0.2438(+)
1982-1986	0.0227	0.1213	0.0108(-)	0.1471(+)
1987-1991	0.0121	0.0764	0.0058(-)	0.0866(+)
1992-1996	0.0125	0.0670	0.0061(-)	0.0749(+)
1997-2001	0.0086	0.0246	0.0043(-)	0.0213(-)
2002-2006	0.0068	0.0137	0.0034(-)	0.0105(-)
2007-2011	0.0060	0.0110	0.0030(-)	0.0080(-)
2012-2016	0.0038	0.0071	0.0018(-)	0.0016(-)
Trend	-0.0030	-0.0268	-0.0014	-0.0318

4.5 Constrained vs unconstrained firms

Investment-cash flow sensitivity occurs when firms are financially constrained. It is argued that a wedge between the internal and external costs of capital causes a firm's investment to depend on the availability of internal funds and such dependence is more pronounced for firms facing greater financial constraints (Fazzari et al. 1988). Kaplan

& Zingales (1997), on the other hand, find that firms that are financially healthy can exhibit a high cash flow sensitivity of investment. In order to study the role of financial constraints on investment demand, researchers offered a variety of *a priori* measures of financing frictions. Conflicting arguments about investment-cash flow sensitivity as evidence of financial constraints arise when one uses different criterion to sort the firms into financially constrained and unconstrained groups. Fazzari et al. (1988) regard firms who retain more earnings and pay less dividends as more constrained and show that low-dividend (constrained) firms display higher cash flow sensitivity of investment. EW (2000) recommend using bond rating as an indicator of firm's financial constraints and find that investment of constrained firms are less sensitive to cash flow. Also Kaplan-Zingales (KZ) index (Lamont et al. 2001), Whited-Wu (WW) index (Whited & Wu 2006) and Hadlock-Pierce (HP) index (Hadlock & Pierce 2010) are used broadly to identify firms' constraint status. In particular, Hadlock & Pierce (2010) sort firms according to KZ, WW and HP indices and reveal that financial constraints do *not* lead to a higher investment-cash flow sensitivity.

To test the implications of the covariance-variance structure on investment-cash flow sensitivity, we sort the firms into financially-constrained and financially-unconstrained according to WW index, KZ index, HP index, bond ratings and dividend payout ratio on an annual basis. The classification scheme is outlined in Appendix 4.A. Information about bond rating starts from mid-1980, hence, we look at the period of 1985-2016. Table 4.4 reports the OLS estimates on cash flow sensitivity and q sensitivity of investment for different subsamples of firms. The cash flow sensitivity estimates for constrained firms range between 0.004 to 0.022 while the estimates for unconstrained vary between 0.014 and 0.049. Consistent with the findings in EW (2000) and Hadlock & Pierce (2010), OLS estimator of investment-cash flow sensitivity does not return larger values for constrained firms with WW-index-, KZ-index-, HP-index- and bond-ratings-measures of financial constraints. We also report the covariance between Q and cash flow with individual and year fixed effect partialling out from Q (denoted as ϕ_{Qcf}) for different subsamples of firms. It is shown that constrained firms which have

Table 4.4: OLS regression for constrained v.s. unconstrained firms

This table reports OLS estimation results during 1985-2016 across groups of financially constrained and unconstrained firms. The dependent variable is capital expenditure scaled by beginning-of-year property, plant and equipment. Independent variables are cash flow and Q. All regressions include firm and year fixed effects. The table report the OLS regression estimates on Q and cash flow, adjusted R square, number of observations, the projection of Q on cash flow with individual and year fixed effect partialling out (denoted as ϕ_{Qcf}) respectively. Firms are categorized as financially constrained according to Whited-Wu (2005) index, Kaplan-Zingales (1997) index, Hadlock-Pierce (2010) index, bond ratings and dividend payout history. ***, **, *indicate significance at the 1%, 5% and 10% levels.

Dependent Variable:	Independent Variables:				
Investment	Q	Cash flow	R_a^2	Obs.	ϕ_{Qcf}
Constrained Criteria					
1. Whited-Wu index					
Constrained firms	0.005***	0.011***	0.309	16639	-0.757***
	(0.000)	(0.002)			(0.283)
Unconstrained firms	0.006***	0.049***	0.401	19149	4.904***
	(0.001)	(0.007)			(0.740)
2. Kaplan-Zingales index					
Constrained firms	0.008***	0.005	0.309	16015	-0.628***
	(0.001)	(0.003)			(0.225)
Unconstrained firms	0.005***	0.015***	0.458	15394	0.753*
	(0.000)	(0.003)			(0.417)
3. Hadlock-Pierce index					
Constrained firms	0.005***	0.004*	0.338	11201	-0.508*
	(0.000)	(0.003)			(0.298)
Unconstrained firms	0.006***	0.033***	0.429	15824	2.264***
	(0.001)	(0.005)			(0.547)
4. Bond ratings					
Constrained firms	0.006***	0.015***	0.339	36320	0.113
	(0.000)	(0.002)			(0.245)
Unconstrained firms	0.006***	0.030***	0.479	11358	2.793***
	(0.001)	(0.006)			(0.514)
5. Dividend ratio					
Constrained firms	0.006***	0.022***	0.275	7792	-0.750
	(0.001)	(0.003)			(0.544)
Unconstrained firms	0.006***	0.014***	0.385	39886	0.539**
	(0.000)	(0.002)			(0.232)

high WW-index, KZ-index, HP-index and no bond-ratings display negative or much lower ϕ_{Qcf}. The exante literature (e.g., Kaplan & Zingales 1997) often attributes the reverse pattern in investment-cash flow sensitivity to its failure to capture the financial status of the firms. However, we find that the negative covariance between cash flow and q, which leads to a downward bias on the estimate of cash flow coefficient, also contributes to the lower investment-cash flow sensitivity for constrained firms. In Table 4.4, we show that the OLS estimates of investment-cash flow sensitivity are largely underestimated for the constrained firms with high WW-index, KZ-index, HP-index and no bond-ratings due to the negative (firms with high WW-index, KZ-index, HP-index) or the low (firms with no bond-ratings) covariance between cash flow and q. Therefore, it offers a re-examination for the argument that low estimated investment-cash flow sensitivity for constrained firms represents its limited capacity to measure the degree of financial constraints faced by firms.

4.6 Monte Carlo design

We use Monte Carlo simulations to assess the performance of OLS estimator, EW estimator and IV estimator (instrumental variables-type estimator) under the classical error and the non-classical error in this section. As in Almeida et al. (2010), we first study the cross-sectional setting, focusing on the performance of OLS estimator and EW estimator. And then we proceed to the panel setting, examining the performance of OLS estimator, EW estimator and IV estimator. We run two sets of Monte Carlo experiments with the simulated data: First, the measurement error is uncorrelated with the true variable or the error is classical. Second, there is a correlation between the measurement error and the true variable (a non-classical error).

4.6.1 The cross-sectional case

We simulate $N = 2000$ individual observations and we repeat the procedures 2000 times before the average is taken over the 2000 simulations. The following outlines our data-generating process. The response variable y_i is generated according to:

$$y_i = \gamma_0 + \chi_i\beta + z_i\alpha + u_i,$$

where χ_i is the mismeasured and unobservable true variable and z_i is the perfectly-measured variable. β and α are coefficients associated with χ_i and z_i respectively. u_i is the regression error in the model. To mimic the variance of investment-to-capital ratio, u_i has a standard deviation of 0.2. The empirical proxy for χ_i is

$$x_i = \chi_i + e_i.$$

As q^K displays high degree of skewness as shown in Table 4.1 and also the EW estimator is built around the notion of high skewness, we modulate the skewness of χ_i by using gamma distributions with the shape parameter of 0.16. χ_i is set to have a standard deviation of $\sigma_\chi = 5$ and e_i is set to have a standard deviation of $\sigma_e = 1$ to emulate the large variance displayed by q^K. Under the classical error,

$$\text{Corr}(e_i, \chi_i) = 0.$$

This classical assumptions are relaxed to allow the measurement error to correlate with the mismeasured true variable where

$$\text{Corr}(e_i, \chi_i) \neq 0.$$

Specifically, measurement error is generated as $e_i = \theta\chi_i + \sqrt{1-\theta^2}\tilde{v}_i$ where θ controls the correlation between measurement error and latent variable. $\tilde{v}_i$ is an i.i.d. with standard normal distribution. The correlation between measurement and latent variable defines the non-classical error. In the following simulation, we set the correlation between non-classical error and latent variable as $\text{Corr}(e_i, \chi_i) = 0.3$. As in Almeida et al. (2010), our simulation considers cross-sectional correlation among regressors. The correlation allows the measurement error to contaminate the estimated slope coefficients on the perfectly-measured variables. The perfectly-measured variable under the classical error is generated as $z_i = \sigma_z(\frac{\rho}{\sigma_\chi}\chi_i + \sqrt{(1-\rho^2)}v_i)$. z_i has a mean of zero and a standard deviation of $\sigma_z = 0.4$. v_i is an i.i.d. term independent of χ_i with standard normal distribution. ρ represents the correlation between mismeasured variable χ_i and perfectly-measured variable z_i. It is allowed to go from -0.3 to 0.3. ρ controls the correlation between marginal q and cash flow in the actual data set. The reasoning behind the negative relationship between cash flow and q is discussed in Section 4.2. For simplity, z_i is generated in a way that it has zero correlation with the measurement error such that $\text{Cov}(z_i, \chi_i) = \text{Cov}(z_i, x_i)$ [11]. The values we choose for (β, α) are (0.05, 0.01). The Monte Carlo simulation output is presented in Table 4.5. We obtain these results by using OLS estimator, GMM3, GMM4 and GMM5 estimators. Note that z is analogous to cash flow in the empirical works, χ is analogous to true marginal q and x is analogous to empirical Tobin's average q. The estimated coefficients on proxy variable x, denoted as β, is analogous to investment-q sensitivity in the empirical case. The estimated coefficients on perfectly-measured variables z, defined as α, is analogous to investment-cash flow sensitivity in the empirical case. For each of the estimator, we present the RMSE (root mean squared errors), bias and its corresponding t statistic for the estimated β and α with different levels of $\text{Corr}(z_i, \chi_i)$. For GMM4 and GMM5 estimators, we also report the rejection rate of 5% J-test, which is the fraction of Monte Carlo trials in which the J-test rejects the model overidentifying restrictions at the 5% significance level.

[11] Although one might expect a positive relationship between cash flow (represented by z_i) and measurement error (represented by e_i), the positive-correlation assumption will only amplify the biases and strengthen our arguments. To achieve zero correlation between z_i and e_i, one needs to partial out the effect of measurement error from χ_i before it's used to generate z_i

Table 4.5: Monte Carlo performance of OLS estimator and EW estimator: cross-sectional data

The results in this table are produced based on 2000 Monte Carlo trials of 2000 individuals. The result is generated for both classical error and non-classical error with the correlation between χ and z running from -0.3 to 0.3. Non-classical error is defined by setting $\mathrm{Corr}(e_i, \chi_i) = 0.3$. β is the coefficient on the true latent variable, which is analogous to the investment-q sensitivity. α is the coefficient on the perfectly-measured variable, which is analogous to the investment-cash flow sensitivity. OLS estimator denotes estimates from regressing y_i on x_i and z_i. GMMn estimator denotes the EW estimator based on the moments up to order n. RMSE (root mean squared error) is the squared root of the average squared deviation from the true value. The bias is the mean deviation from the true value and the corresponding t statistic is reported below. J-test is a test of overidentifying restrictions of the model. Rejection rate of 5% J-test denotes the fractions of Monte Carlo trials that have J-test rejected at the 5% significance level.

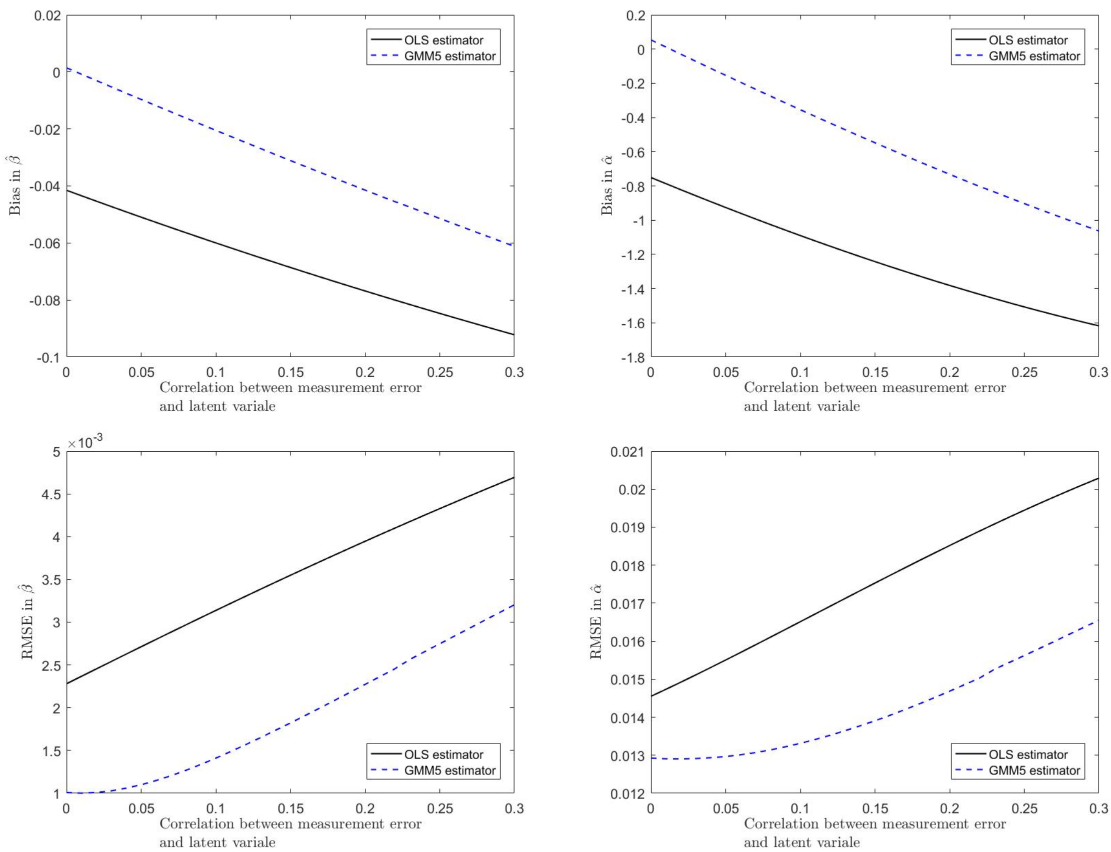
OLS	Classical Errors			Non-classical Errors			*GMM3*	Classical Errors			Non-classical Errors		
Corr(χ, z)	0.3	0	-0.3	0.3	0	-0.3	corr(Q,cf)	0.3	0	-0.3	0.3	0	-0.3
RMSE(β)	0.0043	0.0039	0.0043	0.0093	0.0087	0.0093	RMSE(β)	0.0018	0.0016	0.0018	0.0066	0.0058	0.0063
Bias(β)	-0.0042	-0.0038	-0.0042	-0.0093	-0.0086	-0.0093	Bias(β)	0.0000	0.0000	0.0000	-0.0064	-0.0057	-0.0061
t stat.	-4.1540	-4.0475	-4.1676	-10.0038	-9.7325	-10.0229	t stat.	-0.0002	0.0004	-0.0042	-3.8876	-3.8495	-3.7037
RMSE(α)	0.0207	0.0126	0.0206	0.0356	0.0124	0.0355	RMSE(α)	0.0146	0.0127	0.0146	0.0268	0.0124	0.0259
Bias(α)	0.0158	0.0000	-0.0158	0.0332	0.0000	-0.0331	Bias(α)	0.0000	0.0000	-0.0001	0.0230	0.0000	-0.0219
t stat.	1.1847	-0.0007	-1.1909	2.5732	0.0003	-2.5980	t stat.	0.0024	-0.0018	-0.0071	1.6586	-0.0005	-1.5760
GMM4	Classical Errors			Non-classical Errors			*GMM5*	Classical Errors			Non-classical Errors		
Corr(χ, z)	0.3	0	-0.3	0.3	0	-0.3	corr(Q,cf)	0.3	0	-0.3	0.3	0	-0.3
RMSE(β)	0.0015	0.0012	0.0014	0.0066	0.0056	0.0062	RMSE(β)	0.0014	0.0012	0.0013	0.0065	0.0057	0.0062
Bias(β)	0.0001	0.0001	0.0001	-0.0065	-0.0055	-0.0061	Bias(β)	0.0002	0.0001	0.0001	-0.0064	-0.0056	-0.0061
t stat.	0.0584	0.0918	0.0713	-5.4225	-5.0909	-5.0746	t stat.	0.1237	0.0891	0.0732	-5.2983	-5.301	-5.4259
RMSE(α)	0.0145	0.0127	0.0139	0.027	0.0124	0.0254	RMSE(α)	0.0142	0.0127	0.0141	0.0265	0.0124	0.0257
Bias(α)	-0.0003	0	0.0003	0.0233	0	-0.0217	Bias(α)	-0.0006	0	0.0003	0.0228	0	-0.0219
t stat.	-0.0195	-0.0016	0.0206	1.7029	-0.0003	-1.6386	t stat.	-0.0432	-0.0008	0.0209	1.6821	0.0002	-1.6376
Rejection rate of 5% J-test	0.1775	0.175	0.1635	0.138	0.1795	0.147	Rejection rate of 5% J-test	0.2815	0.3195	0.325	0.334	0.3225	0.338

For the OLS estimator, the downward biases for q coefficients are larger in the case of non-classical error, as proven by Eqn (4.2.9). In both classical and non-classical cases, the downward bias in β causes a upward bias in α only when z and χ are positively correlated. The downward bias in α can be observed when z and χ are negatively correlated and is more pronounced under a non-classical error. For EW estimator, the biases for β and α are close to zero and statistically insignificant under the classical error. However, the downward bias in β is significant when the measurement error is non-classical, which unsurprisingly, leads to a prominent bias on α when z and χ are correlated. Therefore, negative bias in α still exists when there is a negative correlation between z and χ even for EW estimators in the presence of a non-classical error. RMSEs greatly increased in the case of non-classical error as compared to the case of classical error. With regard to the J-test, there is no significant difference between the classical and non-classical error. The results therefore show that J-test is not very powerful in detecting the non-classical error.

To examine the effect of a non-classical error, we allow the correlation between measurement error and true latent variables (denoted as $\text{Corr}(e, \chi)$) to vary between 0 and 0.5. Notably, $\text{Corr}(e, \chi)$ gauge the degree that error can be classified as non-classical. The $\text{Corr}(\chi, z)$ adopts a negative value and stays at -0.3. The other parameters are the same as above. The results are plotted in Figure 4.4. The left graph reports the bias in the coefficient on the latent variables χ and the right graph reports the bias in the coefficient on the perfectly-measured variables z. In the graphs, solid line plots the bias (difference between the estimated and true value divided by the true value) and the RMSE for OLS estimator and dashed line plots the bias and the RMSE for GMM5 estimator (EW estimator) with varying level of $\text{Corr}(e, \chi)$.

The first notable result is that the absolute bias in estimated α and β is increasing with the correlation between measurement error (e) and true latent variable (χ). For both OLS and GMMM5 estimator, the estimated β are biased downward. Due to the negative correlation between z and χ, both OLS and GMMM5 estimator produce a downward bias for α as well. When the measurement error and the true latent

Figure 4.4: Bias and RMSE with a varying degree of correlation



Note: The solid (dashed) line in the top-left graph plots the bias of estimated coefficients on the mismeasured variable for OLS estimator (GMM5 or EW estimator). The bias is computed as difference between the estimated and true value divided by the true value. The solid (dashed) line in the top-right graph plots the bias of estimated coefficients on the perfectly-measured variable for OLS estimator (GMM5 or EW estimator). The solid (dashed) line in the bottom-left graph plots the RMSE (root mean squared error) of estimated coefficients on the mismeasured variable for OLS estimator (GMM5 or EW estimator). The solid (dashed) line in the bottom-right graph plots the RMSE (root mean squared error) of estimated coefficients on the perfectly-measured variable for OLS estimator (GMM5 or EW estimator).

variable are uncorrelated, or the error is classical, the coefficient biases of GMM5 estimator are small. However, the bias for OLS estimator is still large even with zero correlation between measurement error and true latent variable. For example, the true value of α is 0.1. The GMM5 estimator yields an estimate for α of 0.0105 and

OLS estimator yields an estimate of 0.025 when $\mathrm{Corr}(e, \chi) = 0$. As the measurement error begins to display non-classical feature ($\mathrm{Corr}(e, \chi) > 0$), one can observe large biases of estimated α and β for both OLS and GMM5 estimators. For RMSEs, it increases with the correlation between measurement error and latent variable as well for both OLS estimator and GMM5 estimator. When $\mathrm{Corr}(e, \chi) = 0.3$, the root mean squared error for $\hat{\alpha}$ is 0.02 for OLS estimator and 0.017 for GMM5 estimator. Taken together, the results show that non-classical error can bias the estimates of α even for EW estimator as EW estimator fails to purge the measurement error when the error exhibits a correlation with latent variable.

4.6.2 The panel case

The drawback of using instrumental-variables estimator is the assumption of zero serial correlation in the variables. This seems to be too strong a assumption as both market-to-book of asset ratio and market-to-book of capital ratio are highly autocorrelated (see Table 2.1). We simulate a panel with $N = 2000$ individuals and the length of $T = 50$. The response variable is generated according to

$$y_{it} = \gamma_0 + \zeta_i + \chi_{it}\beta + z_{it}\alpha + u_{it},$$

where ζ_i captures the firm-specific fixed effect and is generated as $\zeta_i = \mu_\zeta \sum_{t=1}^{T} z_{it}$. μ_ζ controls the standard deviation of the fixed effect and is set at 0.1. The empirical proxy for χ_i is

$$x_{it} = \chi_{it} + e_{it},$$

where χ_{it} follows an AR(1) process

$$\chi_{it} = \phi_\chi \chi_{it-1} + \eta_{it},$$

where η_{it} is an i.i.d. innovation to this process with zero-mean and unit-variance gamma distribution. ϕ_χ is the autocorrelation coefficient of the process and we set it to be 0.8. To study the case of non-classical error, measurement error e_{it} is assumed to be correlated with χ_{it} and is designed as $e_{it} = \theta\chi_{it} + \sqrt{1-\theta^2}v_{it}$ for $t = 1 \ldots T$ where θ modulates the correlation between measurement error and latent variable and is assumed to be 0.3. Again v_{it} is an i.i.d. across time and across individuals with standard normal distribution. In this manner, e_{it} is automatically set to have serial correlation as χ_{it} is autocorrelated. As in the cross-sectional case, we allow perfectly-measured variable to correlate with latent variable cross-sectionally: $z_{it} = \sigma_z(\frac{\rho}{\sigma_\chi}\chi_{it} + \sqrt{(1-\rho^2)}v_{it})$ for $t = 1 \ldots T$. We experiment with $\rho = -0.3$, $\rho = 0$ and $\rho = 0.3$ respectively. To apply the IV estimator, we consider the equation in first-differences to remove the individual fixed effect and use x_{it-2} as the instrument. As a comparison, we also report the results estimated with EW estimator (GMM5 estimator). The bias and RMSE for OLS estimator, IV estimator, GMM5 estimator of α and β are shown in Table 4.6.

Table 4.6 shows that there is a great improvement in terms of biases for β and α when IV estimator or EW estimator is applied to deal with measurement error in the classical case. RMSEs for β and α are dwarfed by more than a factor of 5 with the application of IV or EW estimator when the error is in the classical nature. Comparing between IV estimator and EW estimator in the classical case, IV estimator performs better as it delivers a lower economic magnitude and a smaller statistical significance (demonstrated by lower absolute value of t statistics) in biases. This could be because IV estimator is better than EW estimator in handling the fixed effects. Nonetheless, both IV estimator and EW estimator produce significantly biased estimates for β when there is correlation between error and latent variable (non-classical error). The bias and RMSE of β for IV estimator or EW estimator has increased by a factor of 10 if the non-classical error is introduced. Again the underestimation for α is significant when the perfectly-measured variable (analogous to cash flow) is negatively correlated with the latent variable (analogous to true q).

Table 4.6: Monte Carlo performance of OLS estimator and EW estimator: panel data

The results in this table are produced based on 2000 Monte Carlo trials of 2000 individuals and 50 periods. The result is generated for both classical error and non-classical error with the correlation between χ and z running from -0.3 to 0.3. Non-classical error is defined by setting $\text{Corr}(e_{it}, \chi_{it}) = 0.3$ for $t = 1 \dots T$. β is the coefficient on the true latent variable, which is analogous to the investment-q sensitivity. α is the coefficient on the perfectly-measured variable, which is analogous to the investment-cash flow sensitivity. OLS estimator denotes estimates from regressing y_{it} on x_{it} and z_{it}. IV estimator denotes estimates based on equation in first-differences with x_{it-2} as the instrument. GMMn estimator denotes the EW estimator based on the moments up to order n. RMSE (root mean squared error) is the squared root of the average squared deviation from the true value. The bias is the mean deviation from the true value and the corresponding t statistic is reported below.

OLS	Classical Error			Non-classical Error		
Corr(χ, z)	0.3	0	-0.3	0.3	0	-0.3
RMSE(β)	0.0018	0.0019	0.0024	0.0043	0.0043	0.0049
Bias(β)	-0.0018	-0.0019	-0.0024	-0.0043	-0.0043	-0.0049
t stat.	-24.7094	-28.2041	-33.5281	-63.8659	-67.9432	-72.8933
RMSE(α)	0.0105	0.0021	0.0065	0.0156	0.0021	0.0115
Bias(α)	0.0104	0.0019	-0.0064	0.0156	0.0019	-0.0115
t stat.	11.0901	2.1594	-6.8393	16.9663	2.1966	-12.5414
IV	Classical Error			Non-classical Error		
Corr(χ, z)	0.3	0	-0.3	0.3	0	-0.3
RMSE(β)	0.0003	0.0003	0.0003	0.0031	0.0030	0.0031
Bias(β)	0.0000	0.0000	0.0000	-0.0031	-0.0029	-0.0031
t stat.	-0.0341	-0.0046	-0.0316	-10.6361	-10.2254	-10.5889
RMSE(α)	0.0012	0.0011	0.0012	0.0076	0.0011	0.0076
Bias(α)	0.0004	0.0000	-0.0004	0.0075	0.0000	-0.0075
t stat.	0.3403	0.0135	-0.3103	6.6997	0.0139	-6.6150
GMM5	Classical Error			Non-classical Error		
Corr(χ, z)	0.3	0	-0.3	0.3	0	-0.3
RMSE(β)	0.0003	0.0002	0.0004	0.0029	0.003	0.0033
Bias(β)	0.0002	-0.0001	-0.0004	-0.0029	-0.003	-0.0033
t stat.	1.3503	-0.7393	-2.7719	-20.2485	-17.8762	-26.6898
RMSE(α)	0.0022	0.0013	0.0012	0.0094	0.0012	0.0062
Bias(α)	0.0019	0.0010	0.0007	0.0094	0.0009	-0.0062
t stat.	1.937	1.1575	0.7546	9.857	1.0734	-6.8234

4.7 Conclusions

In this chapter, we mainly discuss the importance of measurement error in Tobin's empirical average q in explaining the observed time-series and cross-sectional pattern of cash flow sensitivity. We find, via the errors-in-variables theory, that the effect of measurement error in q on cash flow sensitivity depends on the covariance between q and cash flow. The low or negative covariance between q and cash flow accounts for low cash flow sensitivity observed in the recent years and in the financially-constrained subsamples of firms classified as having high WW-index, KZ-index, HP-index and no bond-ratings. Thus, by exploring the variance structure between regressors, we provide an alternative explanation for the observed pattern of cash flow sensitivity.

Furthermore, by examining the classical assumption, we show that a high-order moment-based GMM estimator (EW estimator) can produce biased estimates if the measurement error is non-classical. Hence, the bias in the estimated coefficients for q variable would continue to affect the coefficient estimates for cash flow variable through the their covariance. In other words, the negative covariance between q and cash flow still leads to a downward bias on cash flow coefficients estimated with the EW estimator.

Appendix *4.A*. Financial constraint indices

WW-index classification: We construct an index of the firm's constraint status based on the results shown in Whited & Wu (2006). WW index is computed as $WW = -0.091CF/AT - 0.062DIVPOS + 0.021TLTD/AT - 0.044LNTA + 0.102ISG - 0.035SG$ where CF/AT is the ratio of cash flow to total asset, $TLTD$ is the ratio of the long-term debt to total assets, $LNTA$ is natural log of total assets, $DIVPOS$ is an indicator that takes the value of one if the firm pays cash dividends, ISG is the firm's three-digit SIC-based industry sales growth, SG is firm's sales growth. In each year, firms in the top 30% of WW index are classified as financially constrained and firms in the bottom 30% of WW index are classified as financially unconstrained.

KZ-index classification: Following Lamont, Polk & Saaá-Requejo (2001), we construct KZ index with the firm's financial information. KZ index is computed as $KZ = -1.002CF/K + 0.283MB + 3.139LEV - 39.368DIV - 1.315CH/K$ where CF/K is the ratio of cash flow to capital stock, MB is market-to-book of asset ratio, LEV is total debt (debt in current liabilities plus long-term debt) scaled by stockholder's equity, DIV is the ratio of total dividends (common dividends plus preferred dividends) to capital stock, CH/K is the ratio of cash holdings to capital stock. In each year, we rank firms based on KZ index and assign those in the top 30% as financially constrained and in the bottom 30% as financially unconstrained.

HP-index classification: Following Hadlock & Pierce (2010), we construct HP index as $-0.737 * Firmsize + 0.043 * Firmsize^2 - 0.040Age$ where $Firmsize$ is equal to the natural log of GDP-deflated total asset (in 2010 dollars), Age is the number of years firms are active with a nonmissing stock price in Compustat file. We assign firms in the top 30% of HP index as financially constrained and in the bottom 30% of HP index as financially unconstrained.

Bond-rating classification: Firms that have a credit rating from S&P and issue positive debt are classified as financially unconstrained. Other firms are treated as constrained.

Dividend-ratio classification: Following Chen & Chen (2012), we use the information of dividend history to classify the firms. We sort the firms based on their ratio of dividends (dividends plus repurchase) to capital stock and the firms that are in the bottom 30% of the annual distribution of dividend ratio for consecutive 10 years are treated as constrained firms.

Appendix *4.B.* High-order moment-based estimator

The construction of fourth-order moment-based estimator is based on EW (2000) and we adopt the classical assumption in EW (2000) in this appendix. With (4.2.4) and (4.2.5), we can write down the second-order moment equations:

$$E(\dot{y}^2) = \beta^2 E(\dot{\chi}^2) + E(u^2) \tag{4.7.1}$$

$$E(\dot{x}\dot{y}) = \beta E(\dot{\chi}^2) \tag{4.7.2}$$

$$E(\dot{x}^2) = E(\dot{\chi}^2) + E(e^2) \tag{4.7.3}$$

and the third-order product moment equations:

$$E(\dot{y}^2 \dot{x}_i) = \beta^2 E(\dot{\chi}^3) \tag{4.7.4}$$

$$E(\dot{y}\dot{x}_i^2) = \beta E(\dot{\chi}^3) \tag{4.7.5}$$

We can also come up with the fourth-order product moment equations :

$$E(\dot{y}^3 \dot{x}) = \beta^3 E(\dot{\chi}^4) + 3\beta E(\dot{\chi}^2) E(u^2) \tag{4.7.6}$$

$$E(\dot{y}^2 \dot{x}^2) = \beta^2 [E(\dot{\chi}^4) + E(\dot{\chi}^2) E(e^2)] + E(u^2)[E(\dot{\chi}^2) + E(e^2)] \tag{4.7.7}$$

$$E(\dot{y}\dot{x}^3) = \beta[E(\dot{\chi}^4) + 3E(\dot{\chi}^2) E(e^2)] \tag{4.7.8}$$

The resulting eight equation contains six unknowns $(\beta, E(u^2), E(e^2), E(\dot{\chi}^2), E(\dot{\chi}^3), E(\dot{\chi}^4))$, and it is possible estimate this vector by numerically minimizing a quadratic form that minimizes the asymptotic variance. The same procedure can be applied to the fifth-order or higher-order moment estimators.

Chapter 5

Concluding Remarks

Motivated by the challenges in understanding the relationship between investment-cash flow sensitivities and the firms' financial constraints, Chapter 2 provides an foundation for the role of frictions generated by the real side of economic activities rather than the financial frictions in explaining the firms' investment response to the internal financial resources. While showing that the increasing capital adjustment frictions is responsible for the declining pattern of investment-cash flow sensitivity, it also demonstrates that the increasing costs of capital adjustment can be attributed to the improvement of technology over time. For the sake of corporate policy, firm managers should devote adequate attention to adapting to the adjustment technology (e.g., maintaining a well-trained labor force and streamlining the process of disrupting the old technology) in the current wave of technological changes.

While empirical research faces the task of disentangling the credit-supply effect from the credit-demand effect during the 2007-09 financial crisis, Chapter 3 builds and calibrates a structural model where one can isolate the supply effect by modeling the demand (productivity) shock and credit supply (collateral) shock as two independent random processes. We assess different types of firms' long-run behavior in the context of capital and labor dynamics in the wake of plummeting collateral value.

Chapter 4 examines the endogeneity issue in empirical corporate finance from the perspective of measurement error in variables. It focuses on one channel, the covariance between mismeasured variable (q) and perfectly-measured variable (cash flow), that accounts for the observed pattern of cash flow sensitivity. While most of the error-corrected estimators are proposed based on the classical assumption that the measurement error is independent of q, the presented Monte Carlo experiment shows that the estimators perform poorly in the case that error is not independent of q. This creates a challenge for researchers who attempt to draw conclusions based on the estimation that rely heavily on the use of q.

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