Title
Three Essays on Financial Economics

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Publication Date
2011

Peer reviewed|Thesis/dissertation

Three Essays on Financial Economics

by

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

in

Economics

in the

Graduate Division

of the

University of California, Berkeley

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Spring 2011

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Abstract

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Professor Pierre-Olivier Gourinchas, Co-Chair
Professor Ulrike M. Malmendier, Co-Chair

In this dissertation, I explore the interactions between financial markets and real economy activities. In the first chapter, I use the evidence from an emerging market to study how the development of its financial system could affect activities in its real economy. In the second chapter, I look at excess returns in the US treasury bond market and try to understand the economic fundamentals driving the risk premia. In the final chapter, I examine corporate financing decisions using publicly traded firms in the US. The patterns in their financing decision can be partially explained by the information embedded in the financial market.

To what extent the development of sophisticated financial markets benefits emerging economies is an open question. In the first chapter, I use a unique data set on all currency derivative transactions by non-financial firms in 2006 and 2007 in Colombia to provide new evidence on one aspect of this question: the effect of participation in derivatives markets on firm capital formation. I use a difference-in-difference propensity score matching approach in order to control for self selection and common trends. I find a large positive effect: firms using currency derivatives invest on average 5.7 percent more, which is about 40 percent of their average investment rate. This investment-enhancing effect is entirely driven by firms taking long positions (i.e. dollar buying) in the derivatives market. For firms taking short positions, typically exporters, the use of derivatives does not have any discernible impact on investment. One possible explanation is the asymmetry in the impact of the exchange rate movement on exporting and importing firms.

In the second chapter, I propose a latent variable approach within a present value model to estimate the expected short rate changes and bond risk premia. This approach aggregates information contained in the history of yield spreads and short rate changes to predict future bond excess returns and short rate changes. I find that the factor from Cochrane and Piazzesi (2005) fails to predict bond excess returns when I consider different maturities of the underlying short rate. From the proposed present value model, I find a significant predictable component in short rate changes with R-square ranging from 29 precent to 80 percent, and

a moderate R-square about 12 percent for predicting bond excess returns. Both expected short rate changes and bond risk premia have a persistent component, but bond risk premia are more persistent than expected short rate changes. In addition, the bond risk premia become more persistent as I increase the maturity of the underlying short rate. Finally, I explore the source of the time variation in bond risk premia, and find that monetary policy plays an important role.

In the third chapter, I document a strongly decreasing time trend in firms' leverage ratio at their IPO years over the period from 1975 to 2006. This trend survives when typical factors are controlled for, including industry fixed effect. Furthermore, I find that firms listed more recently are more adverse to debt financing. A deeper examination shows that the risk associated with firm's operation provides a limited explanation for this finding. However, the underpinnings of the observed pattern of firms' leverage ratios at IPO are still largely unresolved.

I dedicate this dissertation to my wonderful family. Particularly to my parents, Yingming Yang and Qi Qu who have given me their fullest support, especially when I made the decision to study abroad. I must also thank my loving girlfriend, Jing Cai, for her patience and understanding. Her smiles and encouragements have helped me so much get through difficult times.

Contents

Acknowledgments

I am very grateful to my two advisors, Pierre-Olivier Gourinchas and Ulrike M. Malmendier, and the committee members, Robert M. Anderson and Adam G. Szeidl, for their continuous guidance, support and encouragement. I am also indebted to Michael Anderson, Barry Eichengreen, Yuriy Gorodnichenko, Herman Kamil, Hayne E. Leland, Martin Lettau, Maurice Obstfeld, and Richard Stanton for very useful comments and discussions.

Chapter 1

Currency Derivatives and Corporate Investment

1.1 Introduction

The role of financial market development for the growth of developing countries has attracted much attention both from economic researchers and policy makers. On the one hand, financial derivatives and capital account liberalization help reduce idiosyncratic risk via hedging, diversification and capital mobility, viewed as potentially important factors explaining recent growth of the global economy. On the other hand, the growth of the financial system can also make emerging economies vulnerable to shocks from outside. This is a particularly large concern given the recent financial crisis, which originated in the US banking system in 2008, but soon spread worldwide following the collapse of large financial institutions. Because the crisis originated in complex derivatives markets, economists and others have begun to reevaluate the costs and benefits of these markets. Much of the existing empirical work on finance and growth performs macro level cross-country analysis (Rajan and Zingales (1998), Levine and Zervos (1998), and Atje and Jovanovic (1993)). These studies, while important, do not inform us about which features of financial development are useful, what are the mechanisms, and how are different firms affected, questions that are potentially important from a policy perspective.

In this chapter, I use micro data from an emerging economy, Columbia, to measure the effect of currency derivatives on firm investment, a key driver of economic growth. My firm level approach adds to the existing macro evidence in two ways. First, it allows meto pay special attention to identifying a causal effect using a nonparametric propensity score matching combined with a difference-in-difference approach. Second, the micro approach makes it possible to explore firm heterogeneity in the effect of derivatives, yielding policy predictions about which firms to target. By focusing on the benefits of currency derivatives, I complete one part of a full cost-benefit analysis of these markets.

My first main result is that participation in the currency derivative market increases the investment rate by 5.7 percentage points, which is about 40% of the average investment rate of firms that participated in the currency derivative market in 2007, and about 60% of the average investment rate of firms in 2007 sample. The estimate is both statistically and economically significant. My second main finding is that there is substantial heterogeneity in the effect of the currency derivative use depending on the positions firms take in the currency derivative market. The effect is significant and large for firms taking buy positions, typically net importers, while I cannot find any discernible effect for firms taking sell positions, typically net exporters.

I explore possible explanations to account for this heterogeneity, and I find that the asymmetry in the impact of the exchange rate movement is likely to be responsible for my finding. Intuitively, exporters face smaller currency risk because appreciations are typically accompanied by domestic booms: the increases in domestic sales can compensate for losses in foreign markets. My results suggest that policies that foster the currency derivative market development such as government subsidy programs for currency derivative trading are beneficial in promoting investment, and hence economic growth in Colombia. Further, policies that target on, or are biased towards, import firms should be more effective and more efficient in stimulating economic growth. This message also sheds light on the importance of the currency derivative market for other emerging economies in the region, because of the representativeness of the data set I use in this chapter.

The key difficulty with identifying the benefits of derivatives for firms in practice is endogenous selection. A firm's choice to enter the currency derivative market is non-random, and depends on firm attributes including currency risk exposure, size, investment opportunities, entry costs, and other management characteristics. This endogeneity problem creates a potential selection bias in derivatives use. Existing firm level studies, including Allayannis and Weston (2001) for the US, Berrospide et al. (2008) and Rossi (2008), find a positive relationship between derivatives use and investment using a linear regression technique. While these results help understand empirical patterns in derivative use, due to selection and possible misspecification of the linear model, they may not identify the causal effect of derivatives.

In this chapter, I use a nonparametric technique, propensity score matching combined with difference-in-difference estimation, to identify the causal effect of derivatives. Matching estimators, especially combined with difference-in-difference techniques, are arguably more appropriate in such a setting. Even though the propensity score matching (PSM) procedure is based on matching firms' observable characteristics, it is an improvement over the standard regression analysis adopted in past literature in two ways. One is that PSM focus the researcher's attention on the comparability of the treatment (currency derivative market participant) and control (nonparticipant) firms. Some firms that enter the currency derivative market are simply not comparable to firms that do not participate in that market and vice-versa. Under a PSM approach, firms that are not comparable are excluded from the analysis and not used to estimate a causal effect. The other advantage is that PSM relaxes the parametric assumptions associated with regression-based techniques such as the linear regression framework. Following a methodology increasingly favored in current statistical literature, I assess the credibility of the matching procedure using a number of balancing tests: absolute standardized bias measure, formal paired t-test, and density plots. Further, the combined difference-in-difference technique makes my results robust to concerns of possible unobservable firm characteristics that share the same time dynamics for both market participants and non-participants. This estimation approach is novel for the analysis of the impact of the currency derivative use on firms' investment behavior.

To fully measure the benefit of derivatives use for the economy, one requires information on derivatives participation for a representative sample of firms. Existing studies mostly focused on large publicly traded companies. These firms are in general more financially sophisticated, and less credit-constrained than an average firm in an emerging economy would usually be. This raises questions as to how applicable the existing results can be for largely small and private firms in an emerging economy such as Colombia or other countries in the region. In contrast, my analysis provides a unique window into the financial risk management practices of non-financial corporations in an emerging market, for two reasons. First, the firm-level information on derivative positions is built from the currency forward transactions reported to the Central Bank of Colombia. This provides a more precise and representative measure of derivative use than the one obtained from financial statements or survey data, which are typically used in the past literature[1]. Second, the use of a large sample of firms covering not only publicly traded firms, but also a broad number of private companies, addresses the concern that the patterns observed for publicly traded firms (typically bigger, more financially sophisticated, and less credit-constrained) might not be representative. Especially in an emerging economy, firms are typically small, financially constrained, and have high growth potentials.

To analyze the impact of currency derivative use, I have used information not only on a firms' decision to participate in the currency derivative trading, but also on the net position a firm takes in the market. That is, I differentiate based on whether a firm is taking a long position on foreign currency derivatives (to offset the domestic currency's depreciation) or is short-selling foreign currency derivatives in net terms (to offset an appreciation). This enables a more nuanced approach to study the ways in which companies use the foreign currency derivatives to mitigate their exchange rate exposure by hedging[2]. More importantly as I will show later, depending on the net positions firms take, there is substantial heterogeneity in the impact of the currency derivative use on firms' investment behavior. To my knowledge, such a pattern has never been documented in past literature. The pattern not only helps us understand the mechanism through which currency derivative use affects firms' investment, but also it suggests more effective and efficient policies and subsidy programs should exploit this heterogeneity to stimulate economic growth.

[1] See Tirole (2005) for a discussion of the problems related to off-balance sheet information of corporations.

[2] Graham and Rogers (2002) argue that in order to identify a more precise picture of the companies' risk management practices, one should compute the net position of the companies in the derivatives markets.

An advantage arises from my focus on the Colombian market. The simplicity of the contracts traded in the derivative market helps me better capture the determinants of participation decisions, and this is the key to the success of the PSM procedure. The US dollar forward is more or less the only type of the contract traded in that market. Options, swaps, interest rate derivatives, OTC interest rate swaps and market-traded fixed income futures are limited if used at all.

Measuring the benefits of currency derivatives is important, because, according to the Bank for International Settlements, the use of currency derivatives by non-financial corporations in emerging markets has surged in recent years. Despite the question's macroeconomic importance, however, there is still little understanding of whether and to what extent firms have benefited from the development of currency derivative markets in these economies.

Prior to the crisis 2008, the Colombian economy shared many features with other emerging economies in Latin American region: high volatility in the exchange rate, rapid development of the financial system, and steady economic growth. Figure 1.1 shows the trading activities in the Colombian currency derivative market from 2000 to 2007. The gross value of contracts traded by non-financial firms reached 2.8 billion dollars in 2007 up from only 0.4 billion dollars in 2000, and the annual total turnover in the market as percentage of GDP rose from around 20% to approximately 80%. Based on the IMF Staff Report of 2008, the Colombian economy experienced steady growth (about 6%) over the period 2003-2007, of which a significant proportion (50%-60%) has been supported by a large increase in private investment. Therefore, understanding the effect of the currency derivative use on firms' investment decisions has the potential to provide key insights into the economic growth of Colombia and other similar economies in the region.

The remainder of the chapter is organized as follows. In Section 1.2 I briefly outline the theoretical background concerning what are the determinants of the participation in the currency derivative market and how the currency derivative use could potentially affect a firm's investment behavior. Section 1.3 introduces the data set employed in the empirical analysis. The details of my empirical strategy are explained in Section 1.4. Section 1.5 presents the empirical results and discusses my findings. Finally Section 1.6 concludes and discusses avenues of future research.

1.2 Background

1.2.1 The Decision to Use Currency Derivatives

Before I can evaluate the effect of currency derivative use, I must first understand why firms use currency derivatives. Currency derivatives are generally viewed as important instruments of corporate risk management to hedge against exchange rate risk. Thus the decision of a firm to use currency derivatives or to refrain from doing so depends not only on whether the firm's cash flow has any exposure to the currency risk, but also on whether hedging against such risk is beneficial. There is a vast literature studying the motivations of a firm to engage in any form of the risk management, and I will only survey it here.

Smith and Stulz (1985) show that bankruptcy costs creates incentives for firms to use currency derivatives if their operations are also exposed to exchange rate risk[3]. By stabilizing a firm's cash flows, hedging decreases the probability and the costs of the financial distress. Many papers use the debt ratio (the firm's leverage) to measure the deadweight costs of financial distress, and some studies have found that hedging increases with the debt ratio, e.g. Graham and Rogers (2002), Purnanandam (2008). Others, however, find no evidence or mixed evidence for the relationship between hedging and leverage position, e.g. Nance et al. (1993) and Geczy et al. (1997). Smith and Stulz (1985) also argue that hedging can reduce the expected tax liability of a firm in the presence of a progressive tax schedule, which makes volatility costly. For such firms, a smoother profit stream creates tax advantages.

How much a firm's cash flow correlates with the exchange rate also affects its incentives to use currency derivatives. For example, importers and exporters can hedge their exchange rate exposure so that importing costs and exporting revenues become less volatile when expressed in domestic currency. It is therefore quite understandable that Geczy et al. (1997) find that firms in the US with extensive foreign exchange-rate exposure are more likely to use currency derivatives.

In the case of emerging markets, evidence concerning firms' financial currency risk management is scarce. Cowan et al. (2005) examine the determinants of the corporate use of currency derivatives by publicly traded Chilean firms. They find that derivatives play a role in insulating the firm-level investment from exchange rate shocks. Using a sample of publicly traded firms in Brazil between 1996 and 2005, Rossi (2007) finds that the decision to use currency derivatives is determined by the costs of the hedging practice (i.e. larger firms are more likely to use currency derivatives) and by the need to offset the exchange rate risk arising from their foreign currency denominated debt. Schiozer and Saito (2005) investigate the determinants of the currency risk management for 57 non-financial firms in Argentina, Brazil, Chile, and Mexico, all of which have issued American Depositary Receipts in international stock markets. They find that these firms use derivatives mainly to hedge the foreign currency debt. They also find that economies of scale, the costs of financial distress, and growth opportunities are important for risk management decisions[4]. Allayannis et al. (2001) examine the currency hedging practice of emerging market non-financial firms in eight East Asian countries over the period 1996 - 1998. They find limited support for the existing theories of derivative use: liquidity-constrained firms with higher investment opportunities do not hedge significantly more than less liquidity-constrained firms in their sample. They also find that firms in East Asia use foreign cash income as a substitute for derivative hedging. Using survey data on the foreign exchange risk management of 223 non-financial firms in

[3]These exogenous costs can include, for example, the costs related to loss of long term relationships with suppliers and customers.

[4]Moguillansky (2002) provides a narrative account of the currency risk management of multinational companies with investments in Latin American countries.

Korea, Kim and Sung (2005) find that firm size and export revenues are the main drivers in the decision to use foreign currency derivatives.

1.2.2 Currency Risk Management and Investment Rate

Why would corporate currency risk management be expected to affect investment behavior? Myers (1977) and Froot et al. (1993) suggest that without hedging, firms are more likely to pursue suboptimal investment projects. Hedging mitigates this underinvestment problem by reducing not only the costs of obtaining external funds, but also a firm's dependence on external funds. A firm with high exchange rate risk exposure has volatile cash flow due to the movement of the exchange rate. Investors will generally discount the firm's asset when it turns to the capital market for their investment project, and this makes the financing expensive and reduces the level of the investment. Moreover, this volatile cash flow makes the firm less dependent on internal fund for investment projects. It has to go to the external capital market often for its funding needs, and it suffers the cost of the external financing for various reasons such as information asymmetry, risky asset discounting, debt overhang, etc.

The corporate currency risk management also helps in reducing the uncertainty of a potential investment project. For instance, when an exporting firm makes an investment, the expected future cash flow of the project has significant exposure to exchange rate fluctuation if the revenue is mostly denominated in foreign currency. Recent studies of investment under uncertainty have focused on the effect of incorporating various types of cost incurred from investments. The types of cost generally include fixed costs, adjustment costs, and costly reversibility, as documented by e.g. Abel and Eberly (1994), Abel and Eberly (1996), and Caballero and Engel (1999). These costs, especially the irreversibility, make an investment project look like a "real option" (e.g Dixit and Pindyck (1994)). Uncertainty increases the wedge between the marginal revenue of capital that justifies investment and the marginal revenue of capital that justifies de-investment, which makes firms refrain themselves from investing or de-investing by expanding the area of inactivity. A decline in uncertainty has two effects: on the one hand, it makes those "wait and see" firms which are close to the boundary that justifies investment start investing. But on the other hand, for firms that are close to the boundary that justifies de-investment will de-invest. The overall effect can thus be ambiguous. Under reasonable parameters, I expect the first effect to dominate, as shown in Bloom (2009). Currency risk management helps firms reduce the uncertainty involved in investment by reducing the exchange rate exposure, and makes them less cautious when investing. Hence it should have a positive impact on the investment rate on average.

Firms in an emerging economy usually have high growth potentials and less financing means. Their growth is often limited due to financial constraints. Firms that actively manage their currency risk exposure via hedging have higher foreign debt capacities. Hedging therefore can help firms seek more capital from abroad and alleviate their financial constraints. This in turn boosts their investment and their future growth. Moreover, when domestic capital is expensive, the foreign debt provides an alternative funding source. Therefore hedging gives firms access to a less costly source of capital. At the same time, hedging also help firms reduce uncertainty in their investment projects. In sum, I expect that the corporate currency risk management should have positive impact on the corporate investment rate. Further, theories, which include both the static model proposed by Froot et al. (1993) and the dynamic model as in Bloom (2009), suggest that a firm's investment decision is generally a highly nonlinear function of firm's characteristics such as risk exposure, financing conditions, investment opportunities, etc. Therefore, it is more appropriate to take a non-parametric approach such as propensity score matching than adopting a linear regression framework to study the impact of currency derivative use.

1.3 Data Sources and Description

1.3.1 Data

My data set consists of two parts. The first part contains transaction level information about the activities in the currency derivative market of Colombian firms for the period 2006-2007. This part of the data set is compiled by the Central Bank of Colombia and covers *all* currency forward contracts signed between a non-financial firm and a domestic bank in 2006-2007. As mentioned earlier, the most common contracts traded in the market are US dollar forward contracts. Thus I will be using the terms "currency derivative user" and the "forward user" as synonyms henceforth. For each derivative transaction, the database reports the date it was signed, its notional principal, the contractual maturity, and whether the corporate took the buying leg (i.e., bought the dollar forward contract) or selling leg (sold the dollar forward contract) of the transaction. Using information on all contracts signed by each firm in 2006-2007, I constructed their total gross buying position; gross selling position and net outstanding position for every month in 2006-2007. A firm was then classified as a *currency derivative user* or *forward user* for a year if it had outstanding forward contracts during that year[5]. In addition, a firm was classified as *a net buyer* (*net seller*) for a year if it had a long (short) dollar forward outstanding position on average during that year. A long position of the dollar forward contract is one that benefits from an appreciation of the US dollar during the horizon of the contract, while a short currency derivative position benefits from an appreciation of the domestic currency, the Colombia peso.

While the data set provides a comprehensive depiction of firms' financial risk management practices in Colombia, it has a couple of limitations. First, it does not include information on the currency derivative trades conducted by domestic firms in the offshore markets, in

[5]Note that according to this definition, a firm could be classified as a forward user in 2007 even if it did not trade in the forward market in 2007. This would be the case, for example, if a firm had contracted currency derivatives in 2006 with settlement dates that extended into 2007 or beyond.

particular, the NDF currency market in New York[6]. Thus, I may be incorrectly classifying a firm as a non-derivative user, when in fact is managing currency risk in offshore markets. Additionally, the database does not identify firms that may be hedging interest rate risk. Several factors suggest, however, that these caveats do not represent an important limitation upon my empirical analysis. First, according to the interviews with market participants, firms that actively manage exchange rate risk in offshore markets tend to do so domestically as well[7]. Possible exceptions are multinational corporations, which sometimes hedge through their parent companies exclusively in the offshore markets. Second, I know from the local intermediaries that the peso interest rate derivative market is almost non-existent and consists mostly of institutional investors.

The second part of the data set includes the balance sheet and the international trading information of both publicly traded and private firms for the period 2006-2007. In addition to basic accounting data, the database includes information on the amount of foreign currency debt contracted abroad[8]. I augment this data set with information on firms' involvement in the international trade. Using the Central Bank's Balance of Payments Trade Registries database, I match information on the exports and the imports for each firm in the sample. I exclude financial firms, since risk management activities of these firms are not directly comparable with those of other firms. I also exclude public utility firms because they are heavily regulated and their accounting statements thus incompatible with those of other firms. Finally I combine the two parts by merging the information on currency derivative activities (if any) and balance sheet and international trading information for every firm in the sample using the NIT (Numero de Identificacion Tributaria), a unique identifier across databases.

1.3.2 Variable Description

Based on the previous literature, there are several important factors that influence firms' decisions to use foreign currency derivatives to manage exchange rate risk. I list them here along with their empirical counterparts. A detailed definition of each variable can be found in Table 1.9.

- Firm size enters into my estimation as a proxy for the cost of hedging or the economies of scale. To capture firm size, I use the natural logarithm of the total assets.

[6]Colombian authorities do not regulate trading in the offshore market. The NDF market for the peso is among the smaller ones within the Latin America, with an average daily turnover of US$50 million. Off-shore NDFs nearly always trade at a premium to local on-shore rates given the lower perceived counter-party credit risk and currency convertibility risk for NDFs, and lower transactional costs (see Lipscomb (2005)).

[7]It is still possible that I misclassify a net buyer to be a net seller or vice-versa if the firm takes different positions in the domestic market and the offshore market.

[8]Data for publicly traded firms comes from Superintendencia Financiera. Additionally, the Superintendencia de Sociedades, another government agency, collects income statements and balance sheets for a large sample of private firms.

- To measure a firm's probability of financial distress, I use two proxies of the borrowing capacity: the leverage ratio (total liabilities over total assets) and the short-term debt ratio (the fraction of total liabilities coming due in less than a year).

- To capture the extent and direction of the direct exposure to foreign currency risk, I constructed three variables: the share of exports flows and import flows in total sales, and the fraction of financial liabilities denominated in foreign currency[9].

- To proxy the growth opportunities of a firm, I used growth rate in the book value of total assets in real terms.

- To account for the availability of the internal funds I used the sum of cash available and the value of short-term investments over short-term liabilities, namely the quick ratio. The quick ratio measures a firm's ability to repay the short-term liabilities with readily available assets.

Due to data limitations, in this chapter I do not test other motives for derivative use discussed in the literature, such as tax-related incentives or managerial wealth incentives. My main variable of interest, the investment rate, is measured as the annual growth rate in property plant and equipment, deflated by PPI. The reason I use the investment rate in real terms is to exclude the valuation effect in my investment rate measure. In my sample, the average investment rate went from 13.6% in 2006 to 9.6% in 2007. This matches the real investment rate in the aggregate level of Colombia from the IMF Staff Report.

To reduce the effect of the data errors or outliers, I exclude observations that fall in the top and bottom 2.5 percentile in the cross-sectional distribution of leverage, quick ratio, asset growth and investment rate. I further clean the data by dropping very small firms (with total asset less than 20 millions pesos, about 10 thousand dollars) and firms that have net export to sales ratio less than -1. There are very small number of firms that participated in the currency derivative market in 2006 but not in 2007. I exclude those firms, because they complicate the identification of the impact of currency derivative use when using Difference-in-Difference estimations, a problem I will discuss again below. To give a sense of the representativeness of my final sample, it contains 13825 non-financial firms, and the total sales account for 70% of Colombian GDP in 2007.

1.3.3 Main Summary Statistics

Table 1.1 provides summary statistics on several indicators of the currency derivative trade by non-financial corporations in 2007[10]. Among the 13825 firms in the sample, 995 firms (about

[9] I am unable to obtain information on the fraction of assets denominated or indexed to foreign currency. Accounting practices do not mandate a currency breakdown of total assets in firms' balance sheet statements, and the Central Bank does not track individual firms' cumulative foreign currency positions abroad.

[10] Of the 1156 firms with outstanding forward positions in 2007, 1092 (95%) actually traded in currency forward markets in 2007.

6.1%) signed forward contracts at least once during 2007. The average (median) firm traded 10.8 (1.2) million dollars in forward contracts, with a median maturity of little less than two months and a half (seventy-five days). The average (median) notional amount traded in forward contracts was large relative to average (median) international trade, which was about 5.6 (0.4) million dollars. Because a majority of contracts had very short maturities, participation in the currency derivative market may not contribute much to reduce cash flow volatility. However, the average firm participating in forward markets signed 23 different contracts during 2007, suggesting the possibility of the rollover strategies. Panel B and C provide more information on the activities in the currency derivative market. As shown in Panel B, during 2007, most of the firms (73%) signed forward contracts by taking a long position on dollar forwards. Panel C shows the average gross (sales plus purchases) outstanding positions at the end of the year expressed in dollars, and the year average.

Table 1.2 displays the mean values for the key variables in the analysis, and reports the differences between the currency derivative market participants and the non-participants. The variables in Panel A and Panel B are measured at the end of 2006 fiscal year. The value of the investment rate, my main variable of interest, is taken at the end of the 2007 fiscal year and summary statistics are presented in panel C of Table 1.2. Considerable insights can be obtained here from simple univariate results. Consistent with earlier studies, firms participating in the currency derivative market are larger than those do not, with an average total assets of US $45 millions and US $5.4 millions, respectively. Possible explanations are that hedging involves set-up costs, and that trading may require a minimum amount for settling contracts.

Summary measures in Table 1.2 also indicate that, in addition to the differences in the costs of implementing a hedging strategy using derivatives, avoiding financial distress could be an important consideration in firms' use of currency derivatives. Firms that use currency derivatives are also more leveraged and their debt profiles have shorter maturities. The average leverage ratio for the currency derivative users is 54.5%, which is statistically significantly higher than the average leverage ratio of 50.3% for the non-users. The higher the firm's leverage ratio and the larger the short term maturity of debt relative to its total liability, the greater is the probability of financial distress. Consequently, the expected costs of the financial distress for those firms are greater, assuming that exogenous bankruptcy costs are constant across firms. Therefore, the more likely the firm is to use currency derivatives, ceteris paribus[11].

Summary statistics related to proxies for investment opportunities and internal wealth also suggest that derivative users may have bigger incentives to avoid underinvestment costs. On the one hand, they seem to have more valuable investment opportunities (as measured by asset growth rates in real term) than non-users, and the difference between the two groups

[11] Many papers use the debt ratio to measure deadweight costs of financial distress and find that hedging increases with the debt ratio (e.g. Graham and Rogers (2002), Purnanandam (2008)). Others, however, find no evidence or mixed evidence for the relationship between hedging and leverage (e.g.Nance et al. (1993), Geczy et al. (1997)).

is statistically significant. On the other hand, currency derivative users keep lower liquid assets compared to non-users as shown by the quick ratio (the sum of cash and short term investment over current liabilities). This suggests that these two groups differ with respect to proxies for short-term liquidity, i.e., in the available internal funds for investment financing.

Finally, the univariate results suggest that derivative users are more engaged in the international trade (they have higher export and import propensities). They are also more heavily exposed to the downside risk of exchange rate depreciation, i.e., they have significantly higher levels of dollar debts.

1.4 Econometric Strategy

In order to identify the causal effect of the use of currency derivatives on a firm's investment rate in Colombia. Ideally, I would want to compare the investment rate of a firm that uses currency derivatives with the investment rate of the same firm if it had not entered the derivative market. While this sort of counterfactual is rarely observable, I can use the propensity score matching technique to construct a control group of non-derivative-user firms that closely match the characteristics of currency derivative users. One or multiple firms are "selected" into the control group if they are sufficiently similar to a currency derivative user on the basis of the key determinants of participation in the currency derivative market. In other words, the goal is to find non-derivative-user firms that are a priori just as likely to be currency derivative users as those firms that really are using currency derivatives. My identification approach has two stages: first, I construct a matched comparison group of non-derivative-user firms based on observables. Then I estimate the effect using the difference-in-difference approach to remove all unobservable effects that have the same time dynamics in the treatment group and the matched control group. I will explain this in greater detail in later section.

1.4.1 Propensity Score Matching

Let $D_{i,t}$ be a dummy variable indicating whether firm i decides to participate in the currency derivative market at time t and let $Y_{i,t}(1)$ denote the firm's investment rate during the period when it uses currency derivatives. If the firm had not used currency derivative, its investment rate would have been to $Y_{i,t}(0)$. The effect of the use of currency derivative at time t on firm investment rate at time t is measured by

$$Y_{i,t}(1) - Y_{i,t}(0).$$

$Y_{i,t}(1)$ is readily observed for firms that are actively involved in currency derivative market. On the other hand, the counterfactual $Y_{i,t}(0)$ is not, which creates a problem of missing data. In general, for any firm one can only observe either $Y_{i,t}(1)$ or $Y_{i,t}(0)$, but not both.

The average effect of the currency derivative use on the derivative-user firms (the average effect of treatment on the treated) is expressed as:

$$
\begin{aligned}
&\mathbb{E}\left(Y_{i,t}(1) - Y_{i,t}(0)|D_{i,t} = 1\right) \\
&= \mathbb{E}\left(Y_{i,t}(1)|D_{i,t} = 1\right) - \mathbb{E}\left(Y_{i,t}(0)|D_{i,t} = 0\right) - \left[\mathbb{E}\left(Y_{i,t}(0)|D_{i,t} = 1\right) - \mathbb{E}\left(Y_{i,t}(0)|D_{i,t} = 0\right)\right].
\end{aligned}
$$

Researchers often substitute $\mathbb{E}\left(Y_{i,t}(0)|D_{i,t} = 0\right)$ for $\mathbb{E}\left(Y_{i,t}(0)|D_{i,t} = 1\right)$. This is problematic if the assignment is nonrandom, which makes the "selection" term inside the square brackets nonzero. A more appropriate construction of the counterfactual requires a careful selection of a control group. Often there are several time-invariant as well as time-variant firm characteristics that would make it an attractive match for a firm that uses currency derivatives. Matching would work well if both the controls (non-users) and the treated firms (users) have the same expected investment behavior as they would if treated firms had never entered the currency derivative market. This is known as the conditional independence assumption (CIA), also sometimes called the "unconfoundedness assumption", formally:

$$
[Y_{i,t}(0), Y_{i,t}(1)] \perp D_{i,t}|X_{i,t-1}, \tag{1.1}
$$

where $X_{i,t-1}$ is a vector of firm characteristics. That is, controlling for the set of firm's characteristics $X_{i,t-1}$, the assignment of currency derivatives participation is random. For the CIA to be satisfied, $X_{i,t-1}$ should contain all the variables that affect both the decision to participate in the currency derivative market and the outcome variable. I model the participation decision and investment decision made in period t is based on the firm's characteristics in period $t-1$ (i.e. $X_{i,t-1}$). The choice of variables to be included in $X_{i,t-1}$ is guided by theory and institutional knowledge, which I have discussed in the earlier sections. An addition requirement of matching is that

$$
0 < \mathbb{E}(D_{i,t} = 1|X_{i,t-1}) < 1. \tag{1.2}
$$

This rules out the perfect predictability of the decision of participation and ensures that the propensity scores of comparison group firms fall within the propensity score distribution of the derivative-user firms. Combine assumption (1.1) and (1.2), I say that the treatment assignment is "strongly ignorable".

An attempt at simultaneously matching along all firm characteristics creates an intractable dimensionality problem. A more elegant solution proposed by Rosenbaum and Rubin (1983) is to match based on an index capturing the information contained in the relevant variables. The index, $p(X_{i,t-1})$, also called a propensity score, is the probability of receiving treatment based on the vector of firm characteristics $X_{i,t-1}$:

$$
P_{i,t} = \mathbb{E}(D_{i,t} = 1|X_{i,t-1}) = p(X_{i,t-1}).
$$

This matching technique allows me to take into account differences in observable characteristics that are relevant to the decision to participate across firms in the database.

1.4.2 Difference-in-Difference Estimation

As discussed in Blundell and Dias (2000), a combination of matching techniques and the difference-in-differences (DID) is likely to improve the quality of non-experimental evaluation studies. Essentially first differencing also removes the unobserved heterogeneity across firms, such as differences in technologies, market power, and/or managerial behavior, and thus provides a cleaner estimate of the causal impact of the derivative use on the investment rate. Unfortunately, the DID estimator does not work perfectly in this context. Ideally, I want the firms not to participate in the currency derivative trading until 2007, so that I can perform the DID on the 06-07 sample where $D_{i,t-1} = 0 \forall i$. The currency derivative market, however, already existed in 2006. Therefore, there were firms already participated in the market in 2006, which makes the differencing over time problematic. Fortunately, I have a large pool of firms that did not participate in the market 2007, and there are very few firms that participated in 2006 but did not participate in 2007. I drop inconsistently participating firms so that firms in the control group did not participate in the market in neither 2006 nor 2007. As for the firms that participated in 2007 (the treatment group), a number of them already participated in 2006. One approach would be to leave these out of the sample. But this would significantly reduce the number of firms in the treatment group, giving mea more imprecise estimated effect. So although keeping these firms in the sample will introduce bias to the estimates, the bias, as I will show later, will go against my results, making my estimates conservative. In a way, one can think of the estimated effect as a lower bound of the true impact of the currency derivative use on firms' investment behavior. Moreover, if I only use PSM estimation, then the estimate does not suffer such a bias. However, the cost of this strategy is that the estimates will be vulnerable to identification issues from the possible firms' characteristics that are unobserved to econometricians.

In the rest of the section, I use a heuristic approach to illustrate the assumptions required in order to identify the effect of currency derivative use on firms' investment, for both PSM and PSM combined with DID estimations. Therefore I can be clear about (i) how PSM combines with DID approach improves the identification concern over the standard PSM and (ii) why it gives mea conservative estimate. Afterwards, I will give the explicit formula for PSM combined with DID estimator.

Heuristic Derivation. Recall the CIA assumption (1.1):

$$\begin{aligned}
&[Y_{i,t}(0), Y_{i,t}(1)] \perp D_{i,t} | X_{i,t-1}, \\
&\Longrightarrow [Y_{i,t}(0), Y_{i,t}(1)] \perp D_{i,t} | p(X_{i,t-1}), \qquad \text{where} \quad p(X_{i,t-1}) = \mathbb{E}(D_{i,t} | X_{i,t-1}).
\end{aligned} \tag{1.3}$$

Let's consider this in a linear regression frame work:

$$Y_{i,t} = \alpha + \beta D_{i,t} + f(p(X_{i,t-1})) + u_{i,t},$$

where $f(.)$ is some function that captures the conditionality. Thus the assumption (1.3) is equivalent as stating $D_{i,t} \perp u_{i,t}$. To see this, notice that $u_{i,t}$ is the only random variable in $[Y_{i,t}(0), Y_{i,t}(1)]$ after conditioning $p(X_{i,t-1})$. Now I can write the PSM estimator as

$$Y_{i,t}(1) - \widetilde{Y_{i,t}(0)} = \beta + f(p(X_{i,t-1})) - f(\widetilde{p(X_{i,t-1})}) + u_{i,t} - \widetilde{u_{i,t}},$$

where $\widetilde{Y_{i,t}(0)}$ is the investment rate of the matched firm. Note that the matching procedure helps mein two ways:

$$\mathbb{E}[u_{i,t} - \widetilde{u_{i,t}}] = 0$$

and

$$\mathbb{E}[f(p(X_{i,t-1})) - f(\widetilde{p(X_{i,t-1})})] = 0. \tag{1.4}$$

Therefore, PSM yields a consistent estimator. So there is no need for DID as things stand to identify the effect of the currency derivative use.

The problem of PSM comes from possible variables that are unobserved by econometricians but affect a firm's participation decision and its investment behavior. In my simple framework, it can be expressed as follows:

$$Y_{i,t} = \alpha + \beta D_{i,t} + f(p(X_{i,t-1})) + g(V_{i,t-1}) + u_{i,t},$$

where $V_{i,t-1}$ represents unobservables, and $g(V_{i,t-1})$ captures the combined effect of $V_{i,t-1}$ on the investment and the ex ante probability of the currency derivative market participation. Note that in this setup Assumption (1.3) no longer holds. It remains that $D_{i,t} \perp u_{i,t}$. In this case, PSM gives

$$Y_{i,t}(1) - \widetilde{Y_{i,t}(0)} = \beta + f(p(X_{i,t-1})) - f(\widetilde{p(X_{i,t-1})}) + g(V_{i,t-1}) - g(\widetilde{V_{i,t-1}}) + u_{i,t} - \widetilde{u_{i,t}}.$$

In such a setting, I no longer have a consistent estimator, because, in general,

$$\mathbb{E}[g(V_{i,t-1}) - g(\widetilde{V_{i,t-1}})] \neq 0.$$

Now if I combine PSM and DID, I have

$$\begin{aligned}
&(Y_{i,t}(1) - Y_{i,t-1}) - (\widetilde{Y_{i,t}(0)} - \widetilde{Y_{i,t-1}}) \\
&= \beta(1 - D_{i,t-1}) + \Big(f(p(X_{i,t-1})) - f(\widetilde{p(X_{i,t-1})})\Big) \\
&\qquad - \Big(f(p(X_{i,t-2})) - f(\widetilde{p(X_{i,t-2})})\Big) \\
&\qquad + \Big[(g(V_{i,t-1}) - g(V_{i,t-2})) - \Big(g(\widetilde{V_{i,t-1}}) - g(\widetilde{V_{i,t-2}})\Big)\Big] \\
&\qquad + \mathcal{N},
\end{aligned}$$

where $\mathcal{N}$ is the noise term. I have to keep in mind that the matching is performed on $p(X_{i,t-1})$. In addition, in the sample, there is no firm that entered the market in 2006 but did not enter it in 2007. Hence $\widetilde{Y_{i,t-1}} = \widetilde{Y_{i,t-1}(0)}$. The matching procedure ensures equation (1.4) holds. Given this, the identification requires

$$\mathbb{E}\left[f(p(X_{i,t-2})) - f(\widetilde{p(X_{i,t-2})})\right] = 0, \tag{1.5}$$

$$\mathbb{E}\left[(g(V_{i,t-1}) - g(V_{i,t-2})) - \left(g(\widetilde{V_{i,t-1}}) - g(\widetilde{V_{i,t-2}})\right)\right] = 0. \tag{1.6}$$

As long as there is no systematic deviation over time in the observed variables, assumption (1.5) is reasonable. In contrast, assumption (1.6) is much stronger. It says that the time trends of the unobservables are on average the same for the treatment group and the matched control group. Thus this assumption would hold, for example, the unobservables are time invariant. Assumption (1.6) shows the limitation of my approach in identifying the impact of the currency derivative use. Crucially for my project, though, the data covers the period 2006-2007. The time span is only 1 year, which limits the concern regarding assumption (1.6). Under assumption (1.5) and (1.6), I can combine PSM with DID to yield a consistent estimator for

$$\beta\left(1 - \mathbb{E}[D_{i,t-1}]\right),$$

which is a *conservative* estimate of the impact because $0 < (1 - \mathbb{E}[D_{i,t-1}]) < 1$. I impose much weaker assumptions than assumption (1.3) to achieve the identification at the cost of obtaining a *conservative* estimate of the impact. I set this procedure as my benchmark because the bias will only make my results stronger. In addition, I will also show the estimation results when using different procedures and different subsamples to demonstrate the robustness of my results. Particularly, I will later look at the estimates when I only include firms that participated in 2007 but not in 2006. I show that the estimates indeed become larger in magnitude as expected, although they become statistically insignificant as a result of increase in the standard errors.

Combined Estimator. I now explicitly show the formula I use to combine PSM with DID. In contrast to standard DID in which one treat each of the firms linearly and with the same weight, the DID estimator paired with PSM allows me to include only derivative-user firms within the common support and picks non-derivative-user firms according to the metric function specific to the matching method. The estimator takes the form:

$$\hat{\beta}_{DDM} = \frac{1}{n_1} \sum_{i \in I_1 \cap S_p} \left[(Y_{i,t} - Y_{i,t-1}) - \sum_{j \in I_0 \cap S_p} W(P_{i,t}, P_{j,t}) \left(Y_{j,t} - Y_{j,t-1}\right) \right],$$

where $I_1 \cap S_p$ is the set of treatment firms (the currency derivative users) that falls within the common support S_p, I_0 is the set of control firms, and n_1 is the number of treatment firms in the common support set. $W(.)$ is is a weighting function that depends on the propensity score distance between the treated and control firms. I apply the Gaussian kernel weighting function

$$W(P_{i,t}, P_{j,t}) = \frac{G\left(\frac{P_{j,t}-P_{i,t}}{a_n}\right)}{\sum_{k\in I_0\cap S_p} G\left(\frac{P_{k,t}-P_{i,t}}{a_n}\right)},$$

where $G(.)$ is the Gaussian normal function, $G(x) = e^{-\frac{x^2}{2}}$, and a_n is a bandwidth parameter (Becker and Ichino (2002)). The estimator for the causal effect of the currency derivative use is $\hat{\beta}_{DDM}$. In order to make statistical inferences from my estimates, the standard error is obtained using the bootstrap procedure.

1.5 Results

1.5.1 Propensity Score Estimation

In this section I report the estimates from the probit model for the likelihood of the currency derivative use in 2007. In Table 1.3, I present the results of three probit regressions, each corresponds to a different indicator of the participation in the currency derivative market. Column 1 displays results where the dependent variable is a binary dummy variable that takes a value equal to 1 if a firm is a currency derivative user and 0 otherwise. In column 2 (3), the dependent variable takes the value of 1 when the firm had, on average, a net buying (selling) position in currency derivative contracts during 2007, and 0 if the firm was not a derivative user in 2007[12]. Results on columns 2 and 3 thus capture both the decision and the direction of the currency derivative use. I measure all independent variables as of the end of fiscal year 2006. To control any industry effects, I include one-digit industry dummies in my regressions[13].

I find that, as previous studies have suggested, firm size is an important determinant of participation in the currency derivative market of Colombia. The effect is robust across all three specifications. The dollar debt ratio also has positive effect on the likelihood of participation in the currency derivative market, though the effect is not significant in the case of net seller firms. I conclude that international trade is a key factor for participation in the currency derivative market. From the coefficient of the estimates, I can infer that firms actively hedge their trade exposure by using dollar forward contracts with offsetting cash payments, thus insuring themselves against the earning or cost volatility in the domestic currency. The coefficient of firm leverage and that of short-term debt ratio capture the effect

[12]The control group remains the same across three specifications. The treatment group, however, changes. This is why I have different numbers of observation across three specifications.

[13]Systematic differences in derivative use across industries may reflect industry specific characteristics associated with either increased overseas foreign exchange rate exposure, incentives for optimal risk reduction or different degrees of exchange rate pass-through.

of financial distress. Looking at the coefficients on asset growth rate and quick ratio, I find that high growth firms and firms with relatively fewer liquid assets (and thus with greater motivation to avoid the cost of external funding by hedging) are more likely to engage in the derivative trading. This result, however, is only significant for firms taking long positions. Overall, my estimates are consistent with the most current research on corporate hedging motivations. This provides a solid foundation for the matching procedure in the next stage. It is worth noting at this stage that I do not have strong evidence of the underinvestment motivation among the net-seller firms, and this foreshadows my discovery later that currency derivative use has no significant effect on the investment rates of these firms.

1.5.2 Matching and Balancing Test

The propensity score matching method provides a reliable and robust method for estimating the effect of the currency derivative use if, conditional on the propensity score, the potential outcomes $Y_{i,t}(1)$ and $Y_{i,t}(0)$ are independent of the incidence of participation in the currency derivative market. Under CIA, variables capturing the motives of the currency derivative use should be balanced between the treatment and control groups. As described in Smith and E. Todd (2005), one way to assess the performance of my propensity score matching is to calculate the standardized differences for the covariates in the probit regression. Specifically, for each covariate, I take the average difference between the treated firms and the matched (reweighed) control firms and normalize it by the pooled standard deviation of the covariate in the treatment and control group samples. It is referred as the absolute standardized bias (ASB). The ASB after matching is calculated using the following equation:

$$ASB(X) = \frac{\frac{100}{n_1}\sum_{i \in I_1 \cap S_p}\left(X_i - \sum_{j \in I_0 \cap S_p}\left(W(P_i, P_j)X_j\right)\right)}{\sqrt{\frac{Var_{i \in I_1 \cap S_p}(X_i) + Var_{j \in I_0 \cap S_p}(X_j)}{2}}}.$$

While there is no clear criterion or statistical inference for the value of the standardized difference, Rosenbaum and Rubin (1985) suggest that a value of 20 is large. In addition to the ASB measure, for each variable entering the propensity score model I perform a formal paired t-test comparison between firms in the treatment group and the matched firms from the control group to satisfy myself that no significant differences exist ex ante. Moreover, I also generate a plot of density of p-score to give a visual impression of how well the matching occurs in my sample. Throughout I impose the common support condition and confine my attention to the matched firms from the control group that fall within the support of the propensity score distribution of the treated group. I choose a bandwidth of 0.005 for the Gaussian kernel as my baseline setting. Following Smith and E. Todd (2005), a trim level of 2% is imposed: dropping 2 percent of firms in the treatment group at which the propensity score density of firms in the control group is the lowest.

Table 1.4 reports the balancing test results based on the Gaussian kernel matching. The

ASB measures are all below 9%(in absolute value) in the matched sample. The substantial bias reduction as a result of adopting the matching method is apparent as I compare the *ASB* measures before and after matching in Table 1.4. The only exception here is that I see the *ASB* measure for imports to sales ratio in the case of net sell increases greatly after matching. One might take this as a signal of potential bad matches. However, I note that the *ASB* measure after matching is still far below 20, the level suggested by Rosenbaum and Rubin (1985)[14], and it also survives from the formal paired t-test. To have a visual sense of the quality of the matching procedure, I present density plots of the propensity score for the treatment group, the matched firms from the control group, and the control group for the case of the currency derivative user in Figure 1.2. I cannot discern much difference in the density plot between the treatment group and their matched counterparts[15]. In Figure 1.3, I produce similar plots of one independent variable, firm size, in the case of net buy[16]. From the previous exercise, I find that firm size is an important factor for the decision to participate in the currency derivative market. It is interesting to see how the difference is reduced after matching. Once again, the results show that the matching procedure dramatically improves the density plot of the derivative-user firms and non-derivative-user firms, despite the fact that the density function of the derivative user group has fatter tails on both sides than that of their matched counterparts. In sum, the quality of the matching procedure is outstanding, and provides a solid foundation for the DID estimation in the next stage.

1.5.3 Difference-in-Difference Estimation Results

After demonstrating the quality of my matching procedure, I am now able to present the DID matching estimates in Table 1.5. The estimated coefficients give the causal effect of currency derivative use on firms' investment rates. The top panel of Table 1.5 reports the estimates with my baseline Gaussian kernel setting of bandwidth and trim level. The estimates show that the average causal effect of currency derivative use on firms' investment rates is about 5.7% of real capital stock. The effect is statistically and economically significant. The average investment rate in 2007 of firms in sample is about 9.6%, and 14.1% for firms that use currency derivatives in 2007. Therefore in the baseline setting the estimate of the effect of the currency derivative use is almost 40% of the average investment rate of firms that use currency derivatives in 2007, or about 60% of the investment rate of an average firm in the 2007 sample. The average effect is even larger when I consider the effect of taking a long position in the currency derivative market. The estimate goes up to a little over 7.3% of real capital stock under this scenario. More interestingly however, the effect of taking a short position in the currency derivative market on average only accounts for about 2.8% of real capital stock, and I cannot distinguish such a small effect from zero in statistical terms. The

[14]I experiment with the Mahalanobis metric, which will be discussed later, to try to improve the matching for imports to sales ratio. It did not change my results.

[15]The graph for the case of net buy and the case of net sell is very similar and not presented here.

[16]The graph of the case of general use and net sell is similar and not presented here.

evidence suggests that the impact of currency derivative use on firms' investment rates is coming primarily from firms that take long positions in currency derivative market.

In sum, I find that the use of currency derivatives helps firms boost their investment levels in Colombia. The effect is both economically and statistically significant. More intriguingly, I find that there is substantial heterogeneity in such effects depending on the positions firms take in the currency derivative market. I see that the effect is large and significant for firms that take a long position, while the effect is small and statistically insignificant for firms that take a short position. I will first demonstrate the robustness of my results then explore possible explanations for the heterogeneity below.

1.5.4 Robustness Check

To check the sensitivity of my results, I take a number of approaches. I first use different bandwidth parameters for the Gaussian kernel applied in the PSM procedure. Then I apply a different matching metric, the Mahalanobis metric, to see if my results are sensitive to the choice of matching metrics. As discussed above, the benchmark estimates are conservative. I further check if the pattern of results is robust when using PSM only and when using different subsamples.

As Smith and E. Todd (2005) stated, kernel matching can be seen as a weighted regression of the counterfactual outcome on an intercept with weights given by the kernel weights. When applying the kernel matching one has to choose both the kernel function and the bandwidth parameter. The choice of kernel function is relative unimportant in practice according to DiNardo and Tobias (2001). The choice of bandwidth parameter is, however, quite important, e.g. Silverman (1986), Pagan and Ullah (1999). The tradeoff is the variance of the estimates and the biases: a large bandwidth yields a smooth density function, and incorporates more information from all possible matches. On the other hand, the probability of the inclusion of some bad matches is also high with a large bandwidth parameter, and this leads to a biased estimate. Therefore, to prevent the choice of bandwidth from undermining my results, I present my estimates for various choices of the bandwidth parameter ranging from 0.001 to 0.009. I only report the results corresponding to the bandwidth parameter values 0.001 and 0.009 in the middle panel of Table 1.5, the results are similar for other parameter values in the range. I find that my general results remain when changing the bandwidth parameters. The average effect of the currency derivative use on the investment rate ranges from 5% to 6%. The average effect of taking a long position can go even higher, as much as 9% when the bandwidth parameter is 0.001. Consistent with my baseline results, the effect for taking a short position in the currency derivative market is still quite low, about 2% or less, and it is statistically insignificant across all bandwidth parameters. I conclude that the results are independent of the choice of the bandwidth parameter.

Second I examine whether the choice of matching metrics will affect my results. There are many different matching metrics that can be applied in the propensity matching framework. Though the kernel metric is the most popular one, other metrics such as the Mahalanobis metric are also commonly used in the empirical exercise, for instance, in the work of Chari et al. (2008). The most notable difference between the two metrics is that the Mahalanobis metric uses the observable covariates directly. The Mahalanobis distance between covariates X_1 and X_2 is defined as

$$\left((X_1 - X_2)^T C^{-1}(X_1 - X_2)\right)^{1/2},$$

where C is the covariance matrix. I would like to show that my results are robust to difference choice of metrics. Following the approach of Chari et al. (2008), in addition to the propensity score, I include the industry dummies into the set where the Mahalanobis metric is applied. This way, the matching will add extra weight on whether firms from the treatment group and matched firms from the control group are from the same industry sector. The standard error from the matching estimation is bootstrapped. The results are shown in the bottom panel of Table 1.5. The results are similar. The effect of taking a long position in the currency derivative market on the investment rate is more than 10% under the Mahalanobis metric and is statistically significant. However the estimates for the other two categories are insignificant.

The sample of baseline estimation excludes the firms that participated in the currency derivative market in 2006 but did not participate in 2007. However, firms that participated in both 2006 and 2007 are included in the treatment group. The reason I only exclude firms that participated in 2006 from the control group is that I have very large number of firms in the control group, about 13000 firms, relative to the number of firms from the treatment group, a little over 1000. Therefore dropping firms from the control group is not going to affect my results either in the probit estimation stage or in the matching stage. However, if I drop the firms that participated in both 2006 and 2007, about two thirds of the observations in the treatment group are eliminated, which has a huge impact on the precision of my estimates. As I discussed before, keeping the firms that participated in 2006 in the DID estimation only makes my estimates conservative. To show that the pattern is robust, I obtain three sets of additional results. First, I report the estimates from PSM without the DID procedure. In this case, I no longer take difference across time, and I do not worry about the effect of currency derivative use being washed away for firms that participated in both years. The estimates, however, are vulnerable to unobserved variables which affect both investment and participation decisions. I report the estimates in the top panel of Table 1.6. I see that the estimates are very similar to my baseline results. The effect of the currency derivative use for firms taking a long position rises to 9.9% from 7.1% of my baseline result and it is statistically significant. The effect of currency derivative use for firms taking a short position is still insignificant and the sign even turns negative. Second, I drop the firms that participated in both years from my baseline sample, and estimate the effect using only PSM. The numbers are listed in the middle panel of Table 1.6. I see that the effect of currency derivative use rises to 11.5%, which mainly comes from the impact on the firms that take long positions: the estimated effect rises to 15.0% from the benchmark result 7.1%. More importantly, the impact on firms that take a short position is small, only 1.3%, and statistically insignificant. One thing to note here is that the number of observations in the treatment group drops significant by about two thirds. Finally, I use PSM together with the DID estimation on the sample that excludes all 2006 currency derivative market participants. Although all estimates become statistically insignificant because of the rise of the standard errors, the magnitude of the estimates remains economically significant, despite being lower relative to the results in the middle panel of Table 1.6 except for the net sellers. In addition, I find that the estimates for general forward users and net buyers are larger than those in the baseline results. The changes in the magnitude are consistent with the argument that the baseline setup provides conservative estimates, although the change is not as larger as expected[17]. Once again the same pattern of heterogeneity in the impact of the currency derivative emerges.

All in all, my results from PSM combined with DID are robust against different bandwidth parameters and different matching metrics. The pattern of substantial heterogeneity in the impact of the currency derivative use is robust across different sub-samples. Therefore, not taking account of this heterogeneity may lead meto miss valuable information related to the identification of the causal effect of the currency derivative use on the investment behavior. Such a pattern, to my knowledge, has never been documented in the past.

1.5.5 Where does the heterogeneity come from?

Why does the effect of the currency derivative use on firms' investment rates differ so much between firms that take a long position and those selling the derivatives? Here I discuss six possible explanations and their empirical evidence.

Matching quality. One might suspect that the matching procedure is not as good for the net sellers firms as for the net buyer firms. As I see in the balancing test section, the ABS measure for the imports to sales ratio does not reduce after matching, which signals possible bad matches for the net seller firms. To address this concern, I use the Mahalanobis metric to add weight for the imports to sales ratio in addition to the p-score and industry dummies. Though the post-matching ABS measure is still higher than the pre-matching level, the magnitude of the post-matching ABS reduces relative to the post-matching level of my baseline case. Yet even now, I do not find any significant impact of the currency derivative

[17] Given that there are two thirds of firms that participated in both periods in the treatment group, when I include only the firms that did not participate in 2006, the magnitude of the estimates should be tripled. For example, the estimate for a general forward user should be around $5.7\%/(1-2/3) \approx 17\%$. In contrast, the estimate is 8.1% in this case. One possible reason is that the estimates when excluding firms participated in both periods become less accurate due to the small sample. Another possibility is that the baseline result is not so conservative as we think. For instance, there might be a learning process for firms to use currency derivatives. Such learning process makes the effect vary over time as firms accumulating experience in the market. As a result, when I take the difference over time for firms that participated in both periods, some of the effect remains. This makes my baseline results less conservative than what the model suggests in the earlier section.

use on investment rates. Therefore I think it is unlikely the heterogeneity is driven by the poor quality of matching for the net-seller firms.

Ex-post exchange rate effect. My analysis on the impact of currency derivative use is a cross-sectional study. Thus, one might think the heterogeneity in the impact comes from the ex-post movements of the exchange rate between Colombian pesos and US dollars. To address such concern, Figure 1.4 gives the exchange rate movements of Colombian pesos in 2007. Colombian pesos experienced a significant appreciation in the first half of 2007. After that the trend reversed until the third quarter, when pesos started to appreciate again over the final quarter of the year. Overall Colombian pesos appreciated about 10% in 2007. If the ex-post movement of the exchange rate is affecting the results, I should expect that firms taking a sell position in the dollar forward contracts would gain more because the movement of the exchange rate was in their favor. But this is the very opposite of the results I in fact find. I take this as solid evidence against the conjecture that the ex-post movement of the exchange rate is driving the results[18].

Interest rate arbitrage. Firms that are taking a long position in the currency derivative market are more likely to engage in cross-border financing to access a low cost funding source, which would enable them to sustain a higher investment rate. A key feature to understand this particular financing strategy by firms is the price distortion in the forward market created by regulatory limits on the bank's net cash foreign currency position, introduced in March 2004. This distortion implies that the forward premium (the implicit devaluation in forward contracts) deviates from the interest rate differential between dollar and peso interest rate (the covered interest parity condition). Figure 1.5 plots the interest rate differential between the on-shore short-term corporate lending rate in the domestic currency and the US prime rate, as well as the average forward premium in forward contracts purchased by the corporate sector with maturity less than a month. For most of the period, the forward premium is below the interest rate differential. By purchasing dollar forward contracts, firms in Colombia are able to create a "synthetic peso loan" at a lower rate from the international capital market without facing any currency exchange rate risk. However, the spread between the interest rate differential and the forward premium reflects various market perceived risks, e.g. counter party risk or currency convertibility risk. One might suspect there would not be much arbitrage opportunity left once the spread is corrected for possible risk premia. Moreover, the "synthetic peso loan" argument applies to all firms with access to the international capital market. If the mechanism fully explains the heterogeneity in the impact, then no other firm's characteristic should affect its position in the market unless the characteristic somehow correlates with whether the firm has access to the international capital market. Recall the results from my probit regressions, a firm's international trading position significantly

[18]Ideally if I had the information about the dates the contracts were signed, I would have computed the realized gains or losses. Unfortunately, that information is not available. Moreover, Colombia peso had been appreciating most of the time except for the period from June to September. Unless the contracts that firms took the buying leg were concentrated during that time, it is unlikely that miscalculation of realized gains and losses is a big concern.

predicts its position in the currency derivative market. Figure 1.6 shows the scatter plot of firms' net trading volume (net exports over sales ratio) and their activities in the currency derivative market (the ratio of total value of net purchases of forward contracts over sales). I observe that the scattered plot concentrates in the first and fourth quadrants, indicating a significant negative correlation between trading positions and hedging positions. Unless importing firms for some reason are more likely to have access to the international capital market than exporting firms, it is difficult to conclude the "synthetic peso loan" is fully responsible for the heterogeneity of the impact documented.

Exporting firms receive trade credits from abroad, which are usually denominated in US dollars. Considering the motivation for hedging, these firms are more likely to take a sell position in the currency derivative market, because the main instrument in the market is the US dollar forward. Importing firms are more likely to take a long position. This is exactly what I see in the data according to Figure 1.6. Based on the results, one might infer that the effect of currency derivative use is strong for importing firms, while almost negligible for exporting firms. This could be one of the explanations for the heterogeneity in the effect of currency derivative use documented in this chaper. This in turn raises the question of why import firms benefit more from the currency derivatives than do export firms? There are several possible reasons. I will examine these one by one.

Foreign denominated liability. Firms have liabilities denominated in foreign currency for various reasons, such as supplier's credits, accessing funds from abroad, or other operational expenses. Such liabilities can be a major risk factor in a country whose economy is vulnerable to negative international shocks which could result in a significant depreciation of the country's currency. And such a risk is quite real in emerging economies. Rossi (2007) studies the currency derivative use for public trade Brazilian firms and finds that the impact of the exchange rate fluctuation on firms' liability is a major concern for Brazilian hedgers. Export firms usually receive trade credits from abroad denominated in foreign currency, which make up a significant part of these firms' profit. Import firms, by contrast, receive few or no trade credits in foreign currency. The trade credits from abroad provide a "natural" hedge for the foreign-currency-denominated liabilities of the exporting firms. As a result, the benefit of engaging in currency derivative trade is small for these firms. However, it is completely the opposite for import firms. They cannot depend on the operational income to hedge the risk from the foreign-currency-denominated liabilities. Thus the currency derivative market is very beneficial to them, as it provides the means for import firms to hedge the currency risk. This might be the mechanism that explains why I find such large difference in estimating the effects of currency derivative use in Colombia. Rossi (2007) shows a negative correlation between the hedging intensity using currency derivatives and the ratio of foreign sales to total sales for Brazilian firms. His finding suggests that firms with "natural" hedge feature have less incentive to hedge the currency risk using currency derivatives. His results seem consistent with what my estimates suggest: the benefit of the currency derivative use for these firms is also limited.

I find, however, that foreign currency denominated liability does not seem to be an important concern in the case of Colombia. Table 1.7 reports the proportion of the amount of the US dollar loans from Colombian banks in the total liability[19]. Panel A. shows the mean and median for currency derivative market participant and their matches from the non-currency-derivative-user group. Panel B. shows the mean and median for export firms across different groups. I see that the average of the foreign denominated liability only accounts for about 2% of the total liability on average, and the median is almost 0%. Similar patterns emerge when I look at different grouping based on firms' participation decisions and their trading positions (Row 5 through Row 8). When I restrict the sample of net export firms with bank dollar debt (Row 9-10), the ratio is about 20% on average. The median is about 15%. The number of firms, however, drops significantly. Panel C. reports the same set of statistics for import firms. There is a common theme at work. Overall I see that foreign currency denominated liability is only a very low portion of total liability because very few firms are able to (or are willing to) borrow in US dollars from banks. Moreover, the difference between net sellers and net buyers, or net export firms and net import firms is also very small. The numbers are very similar if I use firms' total sales instead of total liabilities for the normalization. I also look at the estimates of the currency derivative use for firms that take net sell positions separately by dividing the net sellers into two groups: net sellers with bank dollar debts and those without any bank dollar debt. The proposed explanation suggests that for the group of net sellers without any bank dollar debt, the currency derivative use should have a discernible impact on firms' investment behavior. However, the estimate of the impact for this group is 3.5% (-2.0% for the other group), only 0.7% higher than my benchmark result, and so it remains statistically insignificant (with z-stats less than 0.1). In sum I find that most of the firms in Colombia are not able to borrow in foreign currency from banks. On average, the percentage of the foreign denominated liabilities is very small relative to a firm's total liabilities. This is true even among the firms that participated in the currency derivative market in 2007. This is in sharp contrast to Rossi (2007), Berrospide et al. (2008) and Schiozer and Saito (2005), where the authors consider publicly traded firms in Latin America and find that foreign currency denominated liability is a big concern for those firms. Given the evidence discussed, it therefore is very unlikely the concern about firms' foreign currency denominated liability is driving the heterogeneity in the impact of currency derivative use I document in this chapter.

Financial constraints. One might also suspect that export firms are of a generally better quality than import firms in an emerging economy. Export firms usually have better access to the credit market to finance their operations. It is possible that they are less financially constrained than the import firms. According to Froot et al. (1993), financing frictions are key to the underinvestment problem, which make hedging valuable. Therefore if export firms are less financially constrained, then the underinvestment problem will be less severe

[19]The measure has limitations in capturing the firms' foreign currency denominated liability. It only includes the US dollar loans from banks, but other possible forms of foreign currency denominated liabilities such as suppliers' credits or other non-bank loans are not included in the measure.

for them and the benefits from participating in the currency derivative market will be small. I use two proxies to measure financial constraint across different groups. First, I use firm size, which is the natural log of the firm's total asset. The second measure is constructed following Kaplan and Zingales (2000), the pseudo-KZ index[20]:

$$\begin{aligned}\text{pseudo-KZ} =& -1.001909 \times CF + 3.139193 \times LEV + 0.2826389 \times DACT \\ & - 1.314759 \times CASH + 0 \times DIV,\end{aligned}$$

where CF is measured by the gross profit normalized by the total asset value, LEV is the leverage ratio, and $DACT$ is the growth rate of the total asset, which replaces the market-to-book ratio Q in the original KZ definition to capture the investment opportunity, $CASH$ is the sum of the cash holding and the short term investment divided by the firm's total asset, and the coefficient in front of dividends variable DIV is set to zero. Total 8 reports the mean, median and standard deviation of the two measures across different groups: exporters and importers, net sellers and net buyers, export firms who are also net sellers and import firms who are net buyers. I see that the difference between each group pair is small for both measures of financial constraint, which suggests that export firms and import firms (or net sellers and net buyers) face similar financing conditions in Colombia.

Asymmetry in the effect of exchange rate movement. According to the monetary theory of the exchange rate, the domestic currency is expected to appreciate if domestic economic growth is relatively strong, ceteris paribus. The appreciation of the domestic currency is associated with the improvement of the domestic economy. The increase in domestic demand helps export firms offset, at least partially, the impact of the reduction in the foreign demand caused by the exchange rate appreciation. It is a different story for import firms. Following a similar argument, a depreciation of the domestic currency reflects the weakening of the domestic economy. Import firms suffer from both higher importing costs resulting from the currency depreciation and the reduction in domestic demand because of the deterioration of the economy. The effects are additive for import firms, while they are offsetting for export firms. This asymmetry may explain why export firms benefit less than the import firms when participating in the currency derivative market. The mechanism is supported in Pritamani et al. (2004), and they find some empirical support for the hypothesis I have just suggested by examining the exchange rate exposure of the stock returns for both export firms and import firms. In addition, the asymmetry might be amplified if I consider the intervention of the central bank in the foreign exchange market. In response to a currency appreciation, the central bank has an incentive to devalue its currency to ensure the competitiveness of the local economy in the world market, which further reduces the risks that export firms face. On the other hand, if the currency depreciates significantly, the central bank, especially in emerging economies, is often short on foreign reserves with which to strengthen its currency, and this

[20] I cannot use the exact formula for the KZ index, because most of the firms in sample are private firms, and I do not have information about market values and dividend payments. Based on the data available I follow the definition in Kaplan and Zingales (2000) as closely as possible.

can precipitate a balance of payment crisis. Import firms face more uncertainty in this case. Therefore the asymmetry in the impact of the exchange rate movement between export and import firms is likely to drive the heterogeneity in the impact of currency derivative use on firms' investment. To test this hypothesis, one should look at the cash flow-exchange rate sensitivity for export firms that do not participate in the currency derivative market and compare this with that for import firms that also do not participate. To have a measure of the sensitivity, I need to expand my data set to include longer time series. But such projects are best left to future research.

1.6 Conclusion and Future Work

This study provides a systematic empirical analysis of investment rate differences between firms that use currency derivatives and firms abstaining from the currency derivative market in Colombia. I attempt to identify the causal effect, using a difference-in-difference propensity score matching approach. I then examine the difference in the effect of currency derivative use on firms' investment behavior depending on the positions they take in the currency derivative market.

My results suggest that there is a positive and significant impact of the currency derivative use on firms' investment rates. Moreover, there is substantial heterogeneity in such effects depending on the positions firms take in the currency derivative market. The effect is both statistically and economically significant for firms that take a long position (typically import firms). However, no such effect is discernible for firms that take a short position (typically export firms). I further explore the reasons for this difference in the effect of currency derivative use. Among the explanations I have considered, I find the most plausible candidate driving the heterogeneity in the impact is the asymmetry in the impact of exchange rate movement between export and import firms. Regardless of the underlying causes, my findings imply that failure to account for heterogeneity in the positions firms take in the currency derivative market leads to biased estimates for a significant subset of the sample.

One important message from this study for policy makers is that the development of the currency derivative market is quite beneficial for Colombian economy via promoting investment from private sectors. Further, policies aiming to foster the market such as government subsidy programs should exploit the firm heterogeneity in the impact of currency derivatives to promote economic growth more efficiently and more effectively, e.g. policies or programs biased towards the import sector.

In the future research, I plan to further explore the heterogeneity in the effect of currency derivative use in Colombia. More specifically, I want to expand the data set to include longer time series so that I can examine how robust my findings are over different time periods. In addition, using the time series observations, I am able construct measures such as cash flow-exchange rate sensitivity to test the asymmetry in the impact of exchange rate movement hypothesis directly. Finally, I am very interested in expanding my data set to include the years of 2008 and 2009, from which I hope to evaluate how important and how beneficial the currency derivative market is for an emerging economy facing the global economic crisis.

Table 1.1 Descriptive Statistics on Firms' Activity in Currency Derivative Markets in 2007

	Panel A: Forward Trading		
	Mean	Median	Standard Deviation
Total Forward Trading (in millions USD)	10.8	1.2	45.8
Value of Contract (in millions USD)	0.7	0.2	2.6
Number of Contracts Subscribed	23	7	59
Maturity of Contract (in days)	103	75	99.5
	Panel B: Direction of Forward Trading		
	Buying FX Forward (long dollar position)	Selling FX Forward (short dollar position)	Both Buying and Selling FX Forwards
Number of Firms	723	454	182
Number of Contracts	10,013	12,892	
	Panel C: Outstanding FX Forward Positions		
	Mean	Median	Standard Deviation
Total FW Position [1] Year End(in millions USD)	4.1	0.7	12.1
Total FW Position Year Average(in millions USD)	1.9	0.2	7.1

derivative market in 2007. The data set is compiled by the central bank of Colombia.

1. Notional value of total gross outstanding forward contracts on average during 2007.

Table 1.2 Firm Characteristics of Currency Derivative Users and Non-Users in 2007

Variable	Forward Users 1049	Non-Forward Users 13556	Difference in Means 1/ (Users minus Non-Users)
Panel A: Incentives for Hedging			
Total Assets (in millions of US$)	44.9	5.4	39.5 ***
			(2.48)
Leverage (in %)	54.5	50.3	4.2 ***
			(0.77)
Short Term Maturity of Debt (in %)	86.5	84.2	2.2 ***
			(0.79)
Quick Ratio (in %)	19.3	37.0	-17.7 ***
			(2.13)
Growth in Asset (in %)	19.5	15.3	4.2 ***
			(0.86)
Panel B: Foreign Exchange Rate Exposure			
Exports to Sales Ratio (in %)	20.5	2.7	17.8 ***
			(0.45)
Imports to Sales Ratio (in %)	19.8	6.4	13.4 ***
			(0.13)
Dollarization of Debt (in %)	2.5	0.4	2.0 ***
			(0.16)
Panel C: Outcome Variable			
Investment Rate (in %)	14.1	9.3	4.7 ***
			(1.79)
Fraction of Firms (in %)	7.2	92.8	

Calculations are based on a sample of Colombian nonfinancial firms from Superintendencia Financiera and Superintendencia de Sociedades. The trading activities in the currency derivative market come from the central bank of Colombia. International trade information comes from Colombian central bank's Balance of Payments Trade Registries data base. A firm is classified as a forward user if it had an outstanding US dollar forward contract on average during year 2007. Variables in Panel A. and B. are measured at 2006 year end. Firm's investment rates are measured in year 2007. The last column reports the paired t-test comparisons between the forward user group and non-user group for the observable firm characteristics. Standard errors are reported in parentheses. Asterisks denote significance of differences in means with ***, **, and * indicating significance at the 1%, 5%, and 10% level respectively.

Table 1.3 Probit Regression Estimates on Firms' Likelihood of Using Currency Derivatives in Colombia, 2007

Independent Variables [1]	Any Forward (1)		Net Buying (2)		Net Selling (3)	
Dependent Variable: Indicator of forward use in 2007						
Size	0.022	***	0.014	***	0.003	***
	(0.001)		(0.001)		(0.000)	
Foreign currency debt ratio	0.058	***	0.041	***	0.007	*
	(0.015)		(0.011)		(0.004)	
Export-to-sale ratio	0.088	***	-0.002		0.022	***
	(0.007)		(0.005)		(0.004)	
Imports-to-sale ratio	0.066	***	0.050	***	-0.007	***
	(0.007)		(0.005)		(0.002)	
Leverage	0.031	***	0.020	***	0.003	**
	(0.006)		(0.004)		(0.001)	
Short term maturity ratio	0.031	***	0.013	***	0.006	***
	(0.006)		(0.004)		(0.002)	
Asset growth rate	0.006		0.006	**	-0.001	
	(0.004)		(0.003)		(0.001)	
Quick ratio	-0.006	**	-0.008	***	0.000	
	(0.003)		(0.002)		(0.001)	
Fixed Effects						
Industry sector dummies	Yes		Yes		Yes	
Observations	13825		13507		13104	
Pseudo R2	0.34		0.32		0.48	

Calculations are based on a sample of Colombian nonfinancial firms from Superintendencia Financiera and Superintendencia de Sociedades. The trading activities in the currency derivative market come from the central bank of Colombia. International trade information comes from Colombian central bank's Balance of Payments Trade Registries data base. Independent variables are measured at 2006 year end. Dependent variables from column (1) to (3) are binary indicators for if a firm is a forward user, a net buyer in the currency derivative market and a net seller in the currency derivative market respectively. A constant and a full set of industry dummy variables are included in all three specifications. Marginal effects evaluated at the mean are reported. Heteroskedasticity-consistent standard errors are in parentheses. Asterisks denote significance of coefficients with ***, **, and * indicating significance at the 1%, 5%, and 10% level.

1. See Appendix for a detailed explanation of the independent variables.

Table 1.4 Balancing Tests from Propensity Score Matching

Variable	Mean		%	% Bias	t-test [3]	
	Treated	Matched	Bias [1]	Reduction [2]	t-stat	p-value
Panel A. Any Forwards						
Size	16.64	16.72	-4.7	96.5	-1.03	0.31
Foreign currency debt ratio	2.26	2.17	1.3	95.7	0.23	0.82
Export-to-sale ratio	19.63	17.68	8.2	88.9	1.49	0.14
Imports-to-sale ratio	19.41	20.90	-8.2	88.6	-1.52	0.13
Leverage	54.52	54.28	1.1	93.9	0.25	0.81
Short term maturity ratio	86.56	86.69	-0.6	92.7	-0.16	0.87
Asset growth rate	19.53	19.66	-0.5	96.6	-0.12	0.90
Quick ratio	19.36	20.95	-2.9	90.7	-0.89	0.37
Panel B. Net Buy						
Size	16.76	16.74	1.3	99.3	0.2	0.84
Foreign currency debt ratio	2.13	1.96	2.5	91.2	0.37	0.713
Export-to-sale ratio	6.93	6.96	-0.20	99.3	-0.03	0.98
Imports-to-sale ratio	24.94	25.47	-2.80	97.2	-0.43	0.67
Leverage	55.36	55.84	-2.20	90.3	-0.43	0.67
Short term maturity ratio	86.43	86.89	-2.10	76.1	-0.45	0.66
Asset growth rate	22.22	23.14	-3.60	87.1	-0.68	0.50
Quick ratio	17.69	19.79	-4.00	88.9	-1.17	0.24
Panel C. Net Sell						
Size	16.42	16.50	-5.20	95.4	-0.48	0.63
Foreign currency debt ratio	2.20	2.05	2.10	93.8	0.20	0.84
Export-to-sale ratio	40.20	40.66	-1.70	99.0	-0.14	0.89
Imports-to-sale ratio	7.67	9.51	-13.50	-670.3	-1.38	0.17
Leverage	50.87	49.97	3.80	45.3	0.40	0.69
Short term maturity ratio	86.20	84.75	6.40	17.3	0.73	0.47
Asset growth rate	13.71	13.68	0.10	98.9	0.01	0.99
Quick ratio	26.25	28.09	-3.00	86.3	-0.32	0.75

Calculations are based on a sample of Colombian nonfinancial firms from Superintendencia Financiera and Superintendencia de Sociedades. The trading activities in the currency derivative market come from the central bank of Colombia. International trade information comes from Colombian central bank's Balance of Payments Trade Registries data base. The table reports average values of the key variables between treatment groups and matched control groups measured in 2006 year end. The treatment groups for Panel A. through C. are forward users, forward net buyers, and forward net sellers in year 2007 respectively. The corresponding matched control groups are from firms that did not enter the currency derivative market in year 2007. The matching is performed based on the estimated propensity score from the probit regressions. The Absolute Standardized Bias estimates (ASB) proposed by Rosenbaum and Rubin (1983, 1985) are reported in column %Bias. There is no statistical inference for the ASB esitmates. They suggested a value of 20 is large in magnitude. The last two columns report formal paired t-test of mean values between the treatment and matched control groups.

1. Absolute Standardized Bias (ASB) measure after matching. See paper for the explicit formula.
2. The reduction in ASB measure before and after matching.
3. Formal paired t-test of mean value between treated and comparison (matched) group.

Table 1.5 The Impact of Currency Derivative Use on Corporate Investment

				Common Support		Off Support	
	Matching Estimate	Std. Err.	Z-stat	Untreated	Treated	Untreated	Treated
Difference-in-difference combined with Gaussian kernel matching estimates (baseline)							
Any Forward	0.057	0.029	1.93	12,784	1,021	0	20
Net Buy Position	0.073	0.032	2.29	12,786	707	0	14
Net Sell Position	0.028	0.050	0.56	12,786	233	0	85
Difference-in-difference combined with Gaussian kernel matching estimates (robustness)							
λ = 0.009							
Any Forward	0.054	0.027	2.01	12,784	1,021	0	20
Net Buy Position	0.071	0.031	2.29	12,786	707	0	14
Net Sell Position	0.030	0.045	0.67	12,786	233	0	85
λ = 0.001							
Any Forward	0.063	0.029	2.19	12,784	1,021	0	20
Net Buy Position	0.090	0.039	2.32	12,786	707	0	14
Net Sell Position	-0.025	0.064	-0.39	12,786	233	0	85
Difference-in-difference combined with Mahalanobis metric							
Any Forward	0.037	0.040	0.91	12,784	1,021	0	20
Net Buy Position	0.107	0.048	2.24	12,786	707	0	14
Net Sell Position	0.012	0.061	0.20	12,786	233	0	85

Calculations are based on a sample of Colombian nonfinancial firms from Superintendencia Financiera and Superintendencia de Sociedades for the period 2006-2007. The trading activities in the currency derivative market come from the central bank of Colombia. International trade information comes from Colombian central bank's Balance of Payments Trade Registries data base. The first column reports the estimates of the impact on corporate investment using the propensity score matching combined with diff-in-diff esitmation. The second column reports the bootstrapped standard errors, and the third column gives the correponding Z-stats. The last four columns reports the number of firms from the treatment groups (Treated) and the control groups (Untreated) that lie within the common supports and outside the common supports. The common supports are defnied based on the propensity score estimations (the probit model). The top panel presents the baseline results where Guassian kernel is used in the matching with bandwidth parameter λ = 0.005. The middle panel presents a set of results corresponding to bandwidth parameter λ = 0.009 and λ = 0.001 respectively. The bottom panel reports the results when Mahalanobis metric is used in the matching. For each set of the results, it reports the estimated effect of forward use in general (Any Forward), the estimated effect of taking a long position (Net Buy Position), and the estimated effect of taking a short position (Net Sell Position).

Table 1.6 Robustness: the Impact of Currency Derivative Use

				Common Support		Off Support	
	Matching Estimate	Std. Err.	z-stat	Untreated	Treated	Untreated	Treated
	Propensity score matching estimate on baseline sample						
Any Forward	0.054	0.021	2.57	12,784	1,021	0	20
Net Buy Positio	0.099	0.037	2.72	12,786	707	0	14
Net Sell Positio	-0.020	0.033	-0.60	12,786	233	0	85
	Propensity score matching estimate on subsample of no 2006-participants						
Any Forward	0.115	0.054	2.12	12,784	286	0	43
Net Buy Positio	0.150	0.071	2.11	12,506	208	0	15
Net Sell Positio	0.013	0.049	0.26	11,875	87	0	18
	Propensity score matching combined with diff-in-diff on subsample of no 06-participants						
Any Forward	0.081	0.061	1.33	12,784	286	0	43
Net Buy Positio	0.121	0.102	1.18	12,506	208	0	15
Net Sell Positio	0.039	0.101	0.39	11,875	87	0	18

Calculations are based on a sample of Colombian nonfinancial firms from Superintendencia Financiera and Superintendencia de Sociedades for the period 2006-2007. The trading activities in the currency derivative market come from the central bank of Colombia. International trade information comes from Colombian central bank's Balance of Payments Trade Registries data base. The first column reports the estimates of the impact on corporate investment using the propensity score matching combined with diff-in-diff esitmation. The second column reports the bootstrapped standard errors, and the third column gives the correponding Z-stats. The last four columns reports the number of firms from the treatment groups (Treated) and the control groups (Untreated) that lie within the common supports and outside the common supports. The common supports are defnied based on the propensity score estimations (the probit model). The top panel presents the results from the propensity score matching estimation only on the full sample. The middle panel presents the results from the propensity score matching esitmation only on the subsample where firms that participated in the currency derivative market in both 2006 and 2007 are excluded. The bottom panel reports the results from the propensity score matching combined with diff-in-diff esitmation on the same subsample as in the middle panel. For each set of the results, it reports the estimated effect of forward use in general (Any Forward), the estimated effect of taking a long position (Net Buy Position), and the estimated effect of taking a short position (Net Sell Position).

Table 1.7 Foreign Currency Denominated Liability Ratio in 2007

	Mean	Median	Number of firms
Panel A. Forward Users and Matched Nonparticipants			
Net Sell Firms	0.03	0.00	233
Matched Net Sell Firms [1]	0.02	0.01	233
Net Buy Firms	0.03	0.00	707
Matched Net Buy Firms [2]	0.02	0.01	707
Panel B. Export Firms			
NP Export Firms [3]	0.01	0.00	2630
P Export Firms [4]	0.03	0.00	683
NP Net Export Firms	0.01	0.00	1484
P Net Export Firms	0.03	0.00	340
NP Net Export Firms with BD [5]	0.24	0.13	63
P Net Export Firms with BD	0.20	0.17	58
Panel C. Import Firms			
NP Import Firms	0.01	0.00	5456
P Import Firms	0.03	0.00	955
NP Net Import Firms	0.01	0.00	4484
P Net Import Firms	0.03	0.00	677
NP Net Import Firms with BD	0.17	0.10	140
P Net Import Firms with BD	0.18	0.13	98

Calculations are based on a sample of Colombian nonfinancial firms from Superintendencia Financiera and Superintendencia de Sociedades for the period 2007. The trading activities in the currency derivative market come from the central bank of Colombia. International trade information comes from Colombian central bank's Balance of Payments Trade Registries data base. The table reports means and medians of the proportion of bank dollar loans in the firm's total liability across different groups.

1. Matched firms from the nonparticipant group using the estimated propensity score, which are likely to take net sell positions in the currency derivative market in 2007.

2. Matched firms from the nonparticipant group using the estimated propensity score, which are likely to take net buy positions in the currency derivative market in 2007.

3. Non-participating export firms

4. Participating export firms

5. Non-participating net-export firms with bank dollar debt

Table 1.8 Financial Constraint Measure

	Mean	Median	Standard Deviation
Panel A. Firm Size			
Net Export Firms	15.25	15.16	1.71
Net Import Firms	15.51	15.40	0.82
Net Sell Firms	16.56	16.18	1.75
Net Buy Firms	16.93	16.78	1.54
Net Export Firms (Seller)	16.22	15.92	1.57
Net Import Firms (Buyer)	16.91	16.75	1.52
Panel B. pseudo-KZ Index			
Net Export Firms	1.25	1.25	0.82
Net Import Firms	1.09	1.15	0.83
Net Sell Firms	1.29	1.31	0.82
Net Buy Firms	1.32	1.39	0.66
Net Export Firms (Seller)	1.43	1.38	0.79
Net Import Firms (Buyer)	1.31	1.36	0.65

Calculations are based on a sample of Colombian nonfinancial firms from Superintendencia Financiera and Superintendencia de Sociedades for the period 2007. The trading activities in the currency derivative market come from the central bank of Colombia. International trade information comes from Colombian central bank's Balance of Payments Trade Registries data base. The table reports means, medians and standard deviations of two empirical measures of financial constraint: the firm size and the KZ index presented in Panel A and Panel B respectively. The firm size is defined as the natural logrithm of firm's total assets. The pseudo-KZ index follows the spirit from Kaplan and Zingales (2000):

$$\text{pseudo-KZ} = -1.001909CF + 3.139193LEV - 1.314759CASH + 0.2826389DACT,$$

where CF is the gross profit over total assets, LEV is the leverage ratio, CASH is the sum of the cash holding and short term investment divided by total assets, and DACT is the growth rate of total assets, which replaces market-to-book ratio Q in the original defition of KZ index to capture the investment opportunities. We cannot use the exact formula of KZ index because most firms in sample are private and the information about market values and dividend payments is unavailable. All variables are measured in the year 2007.

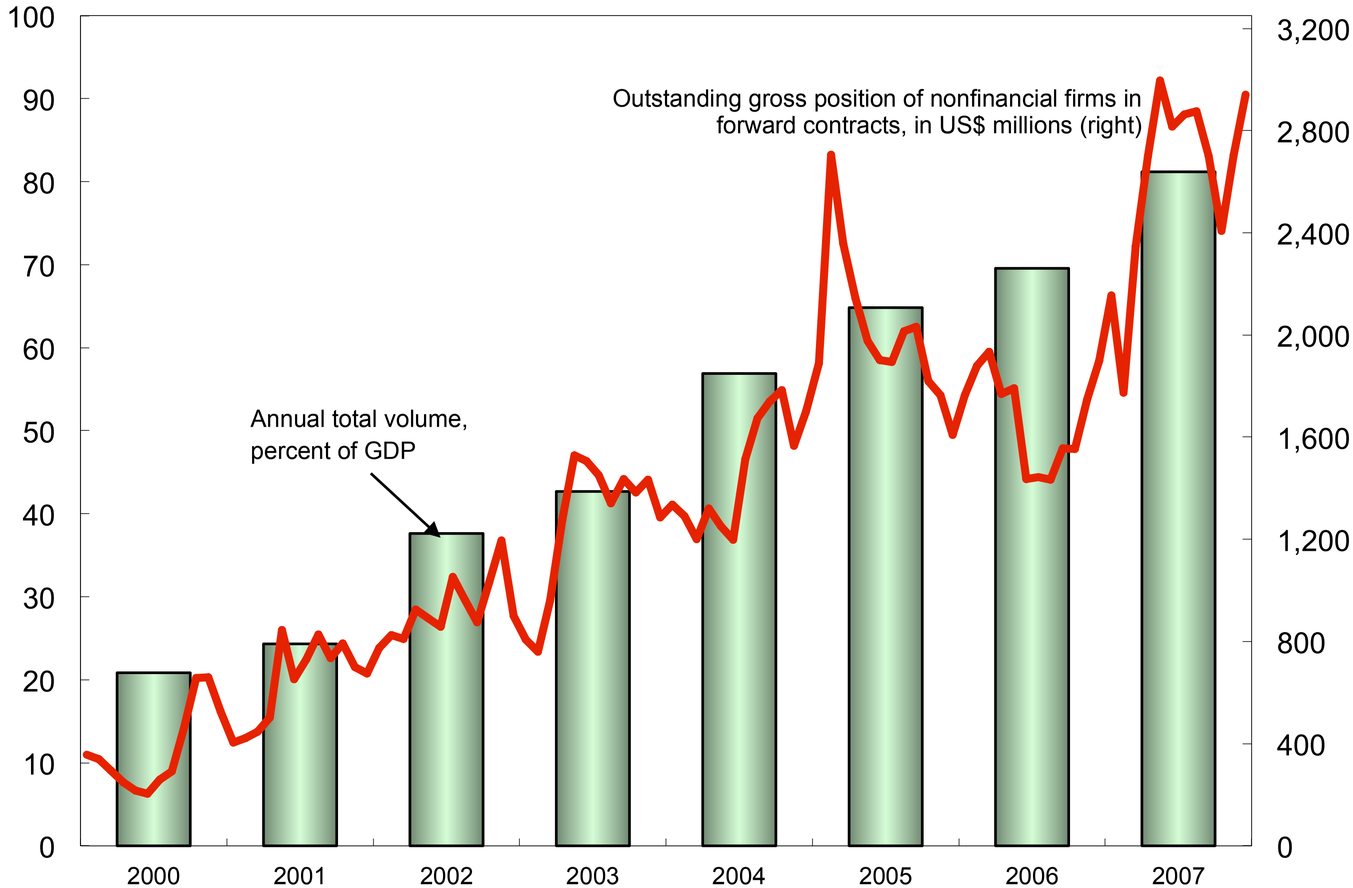
Table 1.9 Variable Definitions and Sources

This appendix provides a summary of all variables used in the empirical analysis and a detailed description of the method of calculation. Calculations are based on a sample of Colombian nonfinancial firms from Superintendencia Financiera and Superintendencia de Sociedades for the period 2006-2007. The trading activities in the currency derivative market come from the central bank of Colombia. International trade information comes from Colombian central bank's Balance of Payments Trade Registries data base.

Variable Name	**Variable Description**
Investment rate	Growth rate in property, plant and equipment relative to previous year in real term [1]
Size	Natural logarithmn of firm's total assets.
Foreign currency debt ratio	Book value of financial debt denominated in foreign currency as a share of total liabilities. It is converted into local currency using end-of-year exchange rate.
Export-to-sale ratio	Exports over total sales from main operating activities.
Import-to-sale ratio	Imports over total sales from main operating activities.
Leverage	Total Liabilities over total assets.
Short Maturity Ratio	Short-term Liabilites over total liabilities
Asset Growth Rate	Growth rate in total assets relative to previous period in real term.
Quick ratio	Sum of cash and short term investment over current liabilities.
Cash Flow	Gross profit over total assets
Economic Sector Dummy	Industry in which the firm has its main operations, according to the one-digit ISIC rev2 classification.

1. To compute the levels in real term, we use the Producer Price Index.

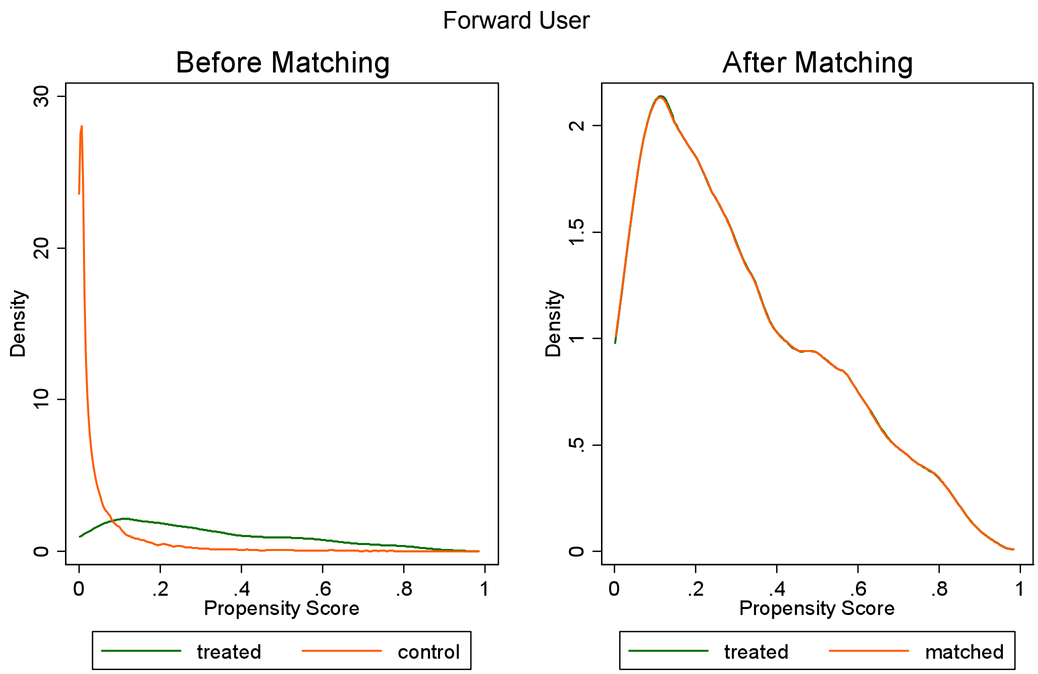
Figure 1.1 Trading Activities in Colombian Currency Derivative Market



This figure depicts the trading activities of nonfinancial coporations in the Colombian currency derivative market over the period 2000-2007. The annual total turnover in the market as percentage of Colombian GDP are presented in the green bar chart. The red line represents the monthly outstanding gross position in forward contacts of nonfinancial coporations in Colombia.

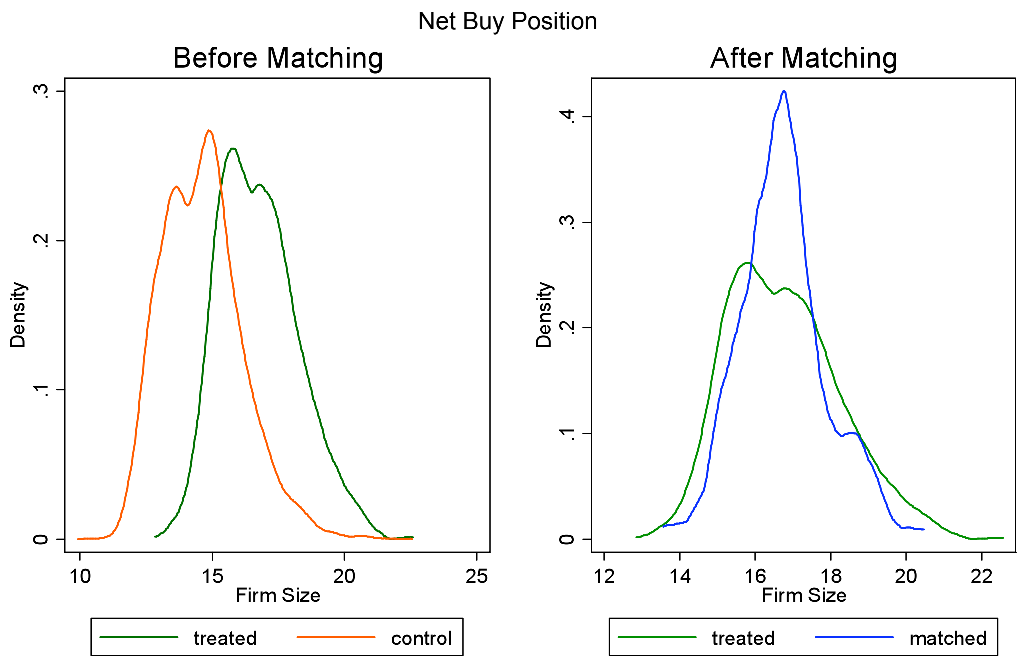
Data source: Central bank of Colombia

Figure 1.2 Propensity Score Density Plot



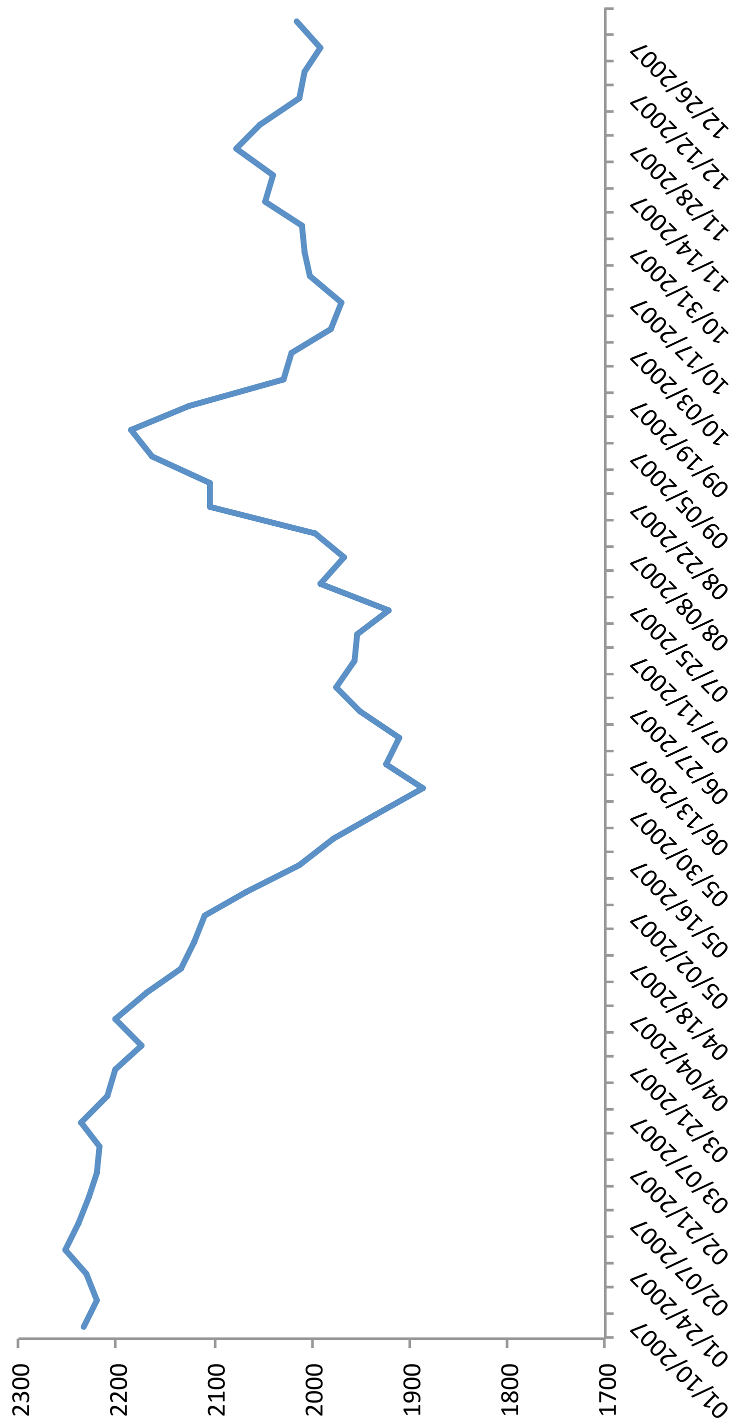
This figure depicts the density plots of the propensity score of participating in the currency derivative market estimated in the probit model. The plot to the left presents the density plot for the treatment group (forward users) and the density plot for the control group (nonparticipants). The plot to the right presents the density plot for the treatment group (forward users) and the density plot for the matched control group (matched nonparticipants). Matching is based on the estimated propensity score of participating in the currency derivative market.

Figure 1.3 Firm Size Density Plot



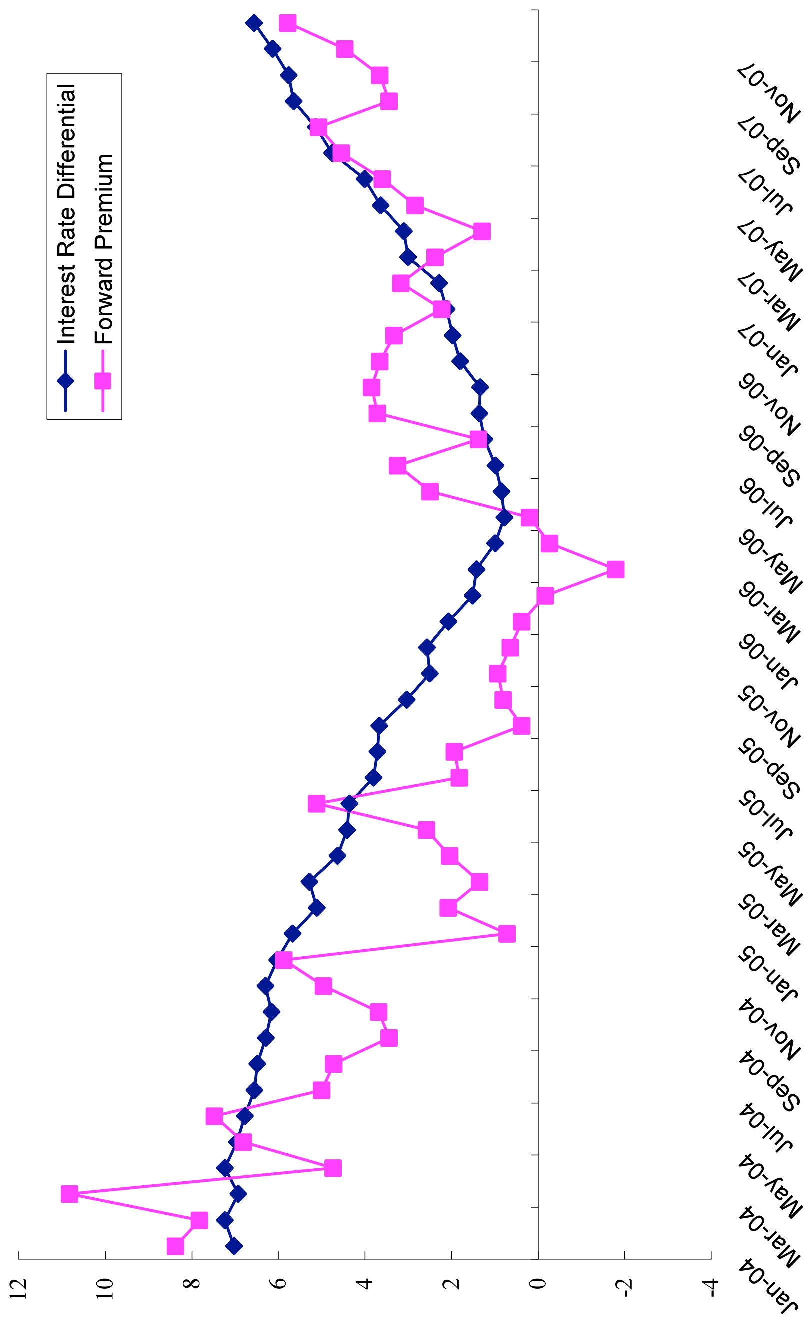
This figure depicts the density plots of firm size. The plot to the left presents the density plot of firm size for the treatment group which consists of firms that take net buy positions in the currency derivative market and the density plot of firm size for the control group which consists of firms do not participate in the currency derivative market. The plot to the right presents the density plot of firm size for the treatment group and the density plot of firm size for the matched control group. Matching is based on the estimated propensity score of taking a net buy position in the currency derivative market.

Figure 1.4 Peso-Dollar Exchange Rate 2007



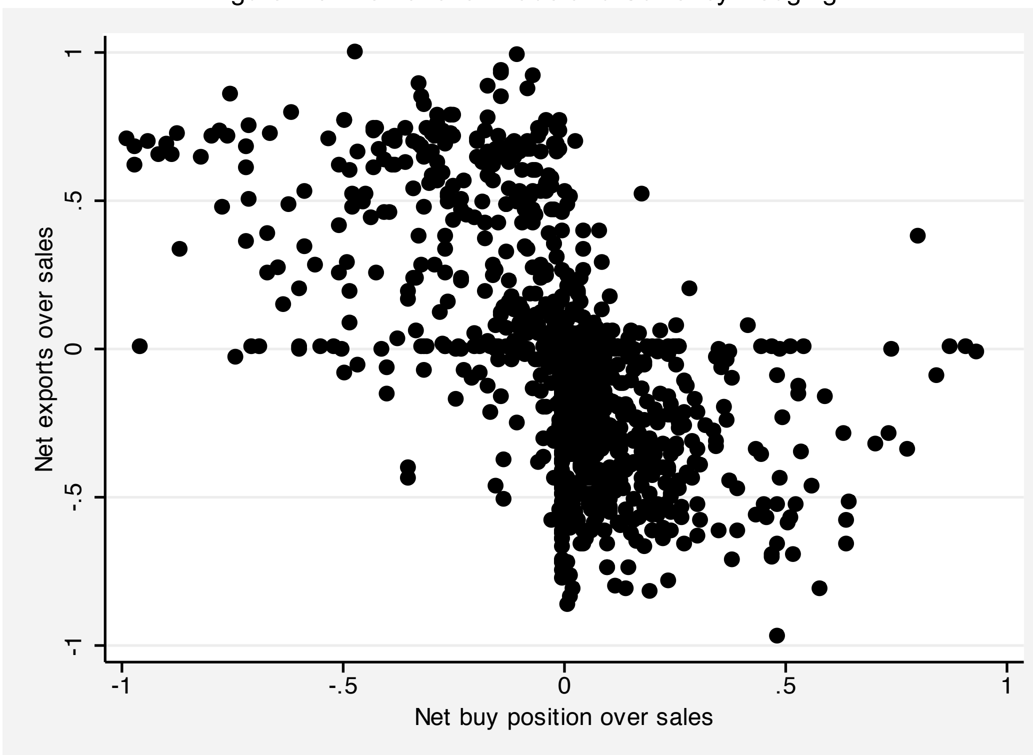
This figure depicts the exchange rate movement between Colombian peso and US dollar in 2007. The exchange rates are the recorded weekely closing prices from Global Financial Dataset. Direction quotation is used from Colombian perspective. An appreciation of Colombian peso is associated with a decline of the exchage rate quoted.

Figure 1.5 Interest Rate Differential and Average Forward Premium



This figure depicts the interest rate differential between the Colombian domestic currency lending rate for corporates and 1-month US dollar Prime rate and the average forward premium over the period 2004-2007. Forward premium is calcuated using simple average forward contracts with maturity of 1 month.
Source: Central bank of Colombia

Figure 1.6 International Trade and Currency Hedging



This figure depicts the scatter plot of firms' currency hedging positions against their trade positions. Firms' currency hedging positions are measured by the net value of US dollar forward contracts purchased over the total sales in 2007. A negative value of the measure indicates the firms took a net sell position in the currency derivative market. Trade positions are measured by the net exports value normalized by the total sales in 2007. Currency derivative trading data comes from central bank of Colombia, and the trade data comes from Balance of Payments Trade Registries.

Chapter 2

Bond Risk Premia and Yield Spread

2.1 Introduction

Time varying risk premia are an important contributor to fluctuations in the US treasury bond market. Understanding their dynamics is important for portfolio choice and pricing assets. It is also crucial for policy makers, who wish to extract market macroeconomic expectations from the bond market and take actions to influence the market. Recent empirical work in the field has documented a significant predictable component in excess returns of US treasury bonds. Cochrane and Piazzesi (2005) find that a significant portion of bond excess returns can be predicted using long maturity forward rates. More importantly, they show that a particular combination of forward rates (the CP factor) has substantial predictive power for bond returns across different maturities. Their findings further strengthen the evidence against the expectation hypothesis in the term structure literature. However, it is not clear what the CP factor represents in economic terms, and how I can interpret time variation in the bond risk premia. Further, it is interesting to see whether the bond risk premia dynamics change when I consider different short rate maturities, because the change in the maturity of the short rate affects both the dynamic of the short rate process and the length of the prediction period. According to the standard factor pricing model if the CP factor predicts excess returns in the bond market, then it must be a factor that is priced by the market. Thus the CP factor should predict excess returns across different maturities, including the maturities of the underlying short rate. As I will show later however, the CP factor fails to predict bond excess returns when I consider short rate maturities less than a year old, which makes their reduced form approach less reliable in studying the dynamics of the bond risk premia. The evidence therefore suggests the dynamics of bond risk premia may vary in response to differing maturities in underlying short rates. Lettau and Wachter (2009) propose a no-arbitrage pricing model, and show that the bond risk premia in their model are driven by a single factor. After calibrating the model, they find a combination of forward rates similar to Cochrane and Piazzesi (2005) that predicts bond risk premia using simulated data. Their result is consistent with Cochrane and Piazzesi (2005), yet the underlying factor that determines bond risk premia is a primitive of their model. The goal of this project is to explore the dynamics of the bond risk premia, from which I want to understand two things: (i) the source of time variation of bond risk premia, and (ii) how the dynamics of bond risk premia change as I vary maturities in the short rate.

I start from a present value model in the spirit of Campbell and Shiller (1991). This model derives from an accounting identity and generates a mechanical relationship among bond risk premia, expected changes in the short rate, and the yield spread. Based on this relationship, I propose a latent-variable approach to study the joint dynamics of expected excess returns and expected changes in the short rate. I treat conditional expected excess returns and expected changes in the short rate as latent variables, which follow an exogenously-specified time-series model. I then construct the likelihood of the model using the Kalman filter technique, and estimate the parameters of the model by means of maximum likelihood. I find that both expected short rate changes and bond risk premia are persistent and time varying, but bond risk premia are more persistent than expected short rate changes. The filtered series for bond risk premia and expected short rate changes are good predictors of realized bond excess returns and realized short rate changes. R^2 is about 12% for excess returns, and ranges from 29% to 80% for expected short rate changes. I find that the persistency of bond risk premia rises as the underlying short rate maturity increases. The autoregression coefficient increases from 0.87 (when the short rate maturity is 3 months) to 0.96 (when the short rate maturity is 12 months). Interestingly, I find that the factor used in Cochrane and Piazzesi (2005) performs poorly in predicting bond excess returns when I shorten the maturity of the underlying short rate, in which case the bond risk premia, based on my estimate, is less persistent. Finally, I find that there is significant co-movement between risk premia shocks and unexpected short rate change shocks. I further provide some evidence for the connection between identified unexpected short rate change shocks and monetary policy shocks, suggesting that monetary policy shocks are responsible for the time variation in bond risk premia.

The present value framework provides a natural channel to capture the co-movement between bond risk premia and expected short rate changes. This helps me understand the source of time variation in bond risk premia. The movement of the short rate is very responsive to the macroeconomic conditions. As Taylor (1993) suggests, movements in the short rate closely relate to the inflation rate and the output gap. Clarida et al. (2000) propose a forward-looking policy rule: the short rate reacts to the expected inflation and the expected output gap. Therefore, exploring the interaction between the short rate change and the bond risk premia will help me understand the source of the time variation in the bond risk premia. Further, Duffee (2009) finds that there is a hidden factor that is important in predicting future interest rates and bond excess returns, yet has zero effect on current yields. The idea is that the hidden factor simultaneously moves the expectation of the future short rate and the bond risk premia in opposite directions. For instance, an increase in the risk premia raises long-term bond yields, whereas the corresponding expected decline of the short rate lowers these yields. Learning the joint dynamics of the short rate change and bond risk premia will help me directly detect this factor and evaluate its significance in explaining the bond risk premia.

The main assumptions I make in this project concern the time-series properties for bond risk premia and the expected short rate change. Under this specification, I can identify both bond risk premia and the predictable componenents of the short rate change. The main contribution of this project is to provide a present value framework that accounts jointly for the predictability of both bond excess returns (bond risk premia) and the short rate change. I model the bond risk premia and expected short rate change as latent processes and use filtering techniques to uncover them. In the present value model, the yield spread is a noisy proxy for bond risk premia when the yield spread also varies due to innovations in the expected short rate change. For the very same reason, the yield spread is also a noisy proxy for the expected short rate change. The proposed framework explicitly takes into account that the yield spread moves due to both bond risk premia and the expected short rate change variation. The filtering procedure assigns yield spread shocks to either bond risk premia and/or expected short rate change shocks. In addition, I am also able to uncover shocks to unexpected short rate changes, as well as correlations among different shocks. According to the policy rule suggested by Taylor (1993), the short rate should be very responsive to movements of macroeconomic variables. Among others, Ang and Piazzesi (2003) find that the Taylor rule fits the short rate movement well. Therefore, the correlations of shocks to short rate changes with bond expected excess returns will help me understand the source of bond risk premia. This is especially intriguing because, from the model, I am able to identify the correlation of expected short rate change shocks with bond risk premia shocks, as well as the correlation of unexpected short rate change shocks with bond risk premia shocks. This helps me understand what kind of short rate change shocks contribute more to the variation of bond risk premia. I then link the identified shocks to monetary policy shocks to provide an economic interpretation of the time varying risk premia in the bond market.

There are two important aspects that distinguish this project from standard affine factor models in the term structure literature. First, the latent variables in my model have specific economic interpretations, which is key to understanding sources of time variation in bond risk premia. In contrast, standard affine factor models usually exact factors from the yields using a generic approach, such as principle component analysis. The names of the factors come from the way they affect the yield curve (i.e. the "level" factor, the "slope" factor, or the "curvature" factor). Therefore, these factors do not help us explore the economics behind the dynamic of bond risk premia. Second, the standard latent factor approach generally assumes measurement errors in the yields to achieve the identification, because the number of factors are usually less than the number of yields with different maturities. Theoretically, I only need the same number of yields to back out the underlying factors assuming the mapping is invertible. If there are more yields than the number of factors, I have an over-identification issue. In addition, these measurement errors often have very simple structure for tractability such as the IID assumption, and the orthogonality assumption among each other. Sometimes, researchers even pick the yields that are measured with error. Such choice seems arbitrary, and the restriction cannot be imposed by any economic theory. In addition, according to Duffee (2009), the plausible measurement error in the Treasury yields is on the order of only a few basis points. Therefore, assumptions of measurement errors are problematic and the simple structure imposed on them in the standard latent factor model could throw away important information contained in the yields. As I will show later, shocks to unexpected short rate change in my model, which could be classified as measurement errors otherwise, are important to explain the time variation in the bond risk premia.

The filtering technique adopted in this project is not new to the asset pricing literature. van Binsbergen and Koijen (2010) use similar framework to study expected returns and expected dividend growth rates of the aggregate stock market. Latent variable approach is often used in factor models in term structure studies, for instance, Dai and Singleton (2000), Ang and Piazzesi (2003) and Christensen et al. (2007). Or, sometimes, the factors are defined to match a specific functional form for the yield curve. Christensen et al. (2007) derive an affine factor model in which yields follow the function form of Nelson and Siegel (1987). Moreover, Cochrane and Piazzesi (2005) and Cochrane (2008a) show that standard factors in the term structure literature: the level, slope, and curvature are not related in the return-forecast factor. In contrast to standard factor approach, I propose a structural model for bond returns and short rate changes directly and study their dynamics. The model in this project is built on low-order autoregressive process for bond risk premia and expected short rate changes. However it admits an infinite-order VAR representation in terms of short rate changes and yield spreads, as shown in Cochrane (2008b). The latent-variable approach aggregates the history of yield spreads and short rate changes to estimate bond risk premia and expected short rate changes. Instead of adding lags to a VAR model, I am expanding the information set to predict bond returns and short rate changes while keeping the model as parsimonious as possible.

The chaper proceeds as follows. In section 2.2, I first explain the Campbell and Shiller (1991) present value model. Then, I use it to show how the CP factor fails to capture the bond risk premia for different maturities of the short rate. Section 2.3 explains the data and estimation procedure for state space model based on the Campbell and Shiller (1991) identity of the yield spread. Section 2.4 presents and discusses the results. Section 2.5 explores the link between bond risk premia and the monetary policy. Finally, section 2.6 concludes.

2.2 Yield Spread and Interest Rate Forecast

I use the notation, $p_{n,t}$, for log price of a zero-coupon bond at time t with remaining maturity n. The log yield becomes

$$y_{n,t} \equiv -\frac{1}{n} p_{n,t}.$$

Let $s_{n,t}$ be the yield spread between an n-period bond and 1-period bond (the short term bond)

$$s_{n,t} \equiv y_{n,t} - y_{1,t}.$$

One has to make a note that the time unit is the underlying short term bond maturity. For example, if the short term bond maturity is 1 month, then expression $t+1$ means one month ahead; if the short term bond maturity is 3 months, then $t+1$ means a quarter ahead. I write the log holding period return from buying an n-period bond at time t and selling it as an n-1 period bond at time t+1 as

$$r_{n,t+1} = p_{n-1,t+1} - p_{n,t}.$$

I can write the yield spread in the following expression

$$s_{n,t} = \left(\frac{1}{n}\right) \mathbb{E}_t \left[\sum_{i=1}^{n} [(n-i)\Delta y_{1,t+i} + (r_{n+1-i,t+i} - y_{1,t+i-1})] \right]. \tag{2.1}$$

The above expression, which is derived from the accounting identity, serves as the foundation of the latent variable model. In addition, the yield spread could also be linked to the change in the long term yield

$$\mathbb{E}_t[y_{n-1,t+1} - y_{n,t}] = \frac{s_{n,t}}{n-1} - \mathbb{E}_t \left[\frac{r_{n,t+1} - y_{1,t}}{n-1} \right]. \tag{2.2}$$

Both equation (2.1) and (2.2) are used to test the Expectation Hypothesis in Campbell and Shiller (1991). They run the following regressions

$$s^*_{n.t} = \mu_n + \gamma_n s_{n,t} + \epsilon_{n,t},$$
$$y_{n-1,t+1} - y_{n,t} = \alpha_n + \beta_n \left(\frac{s_{n,t}}{n-1}\right) + \epsilon_{n,t},$$
$$\text{where } s^*_{n,t} \equiv \sum_{i=1}^{n-1} (1 - i/n)\Delta y_{1,t+i}.$$

Under the expectation hypothesis bond expected excess returns are constant/unpredictable, so I expect $\beta_n = \gamma_n = 1$. However, Campbell and Shiller (1991) shows that estimates of γ_n are significantly less than 1 but positive, while estimates of β_n are negative for most of the time. One important missing element in their specifications is a proxy for bond risk premia. It is interesting to see how their results change when some proxy is used to control for bond expected excess returns. Such procedure provides a natural way to evaluate the performance of a proxy for bond expected excess returns. Moreover, it will give the confidence for applying the filtering technique to uncover bond expected excess returns at later stages since the latent variable model is based on equation (2.1). Cochrane and Piazzesi (2005) find that a single factor, referred to as the CP factor henceforth, drives bond risk premia across all maturities. Therefore I take the CP factor as a proxy for the expected excess return part and run the following regressions

$$s^*_{n.t} = \mu_n + \gamma_n s_{n,t} + \phi_n x_t + \epsilon_{n,t},$$
$$y_{n-1,t+1} - y_{n,t} = \alpha_n + \beta_n \left(\frac{s_{n,t}}{n-1} \right) + \psi_n x_t + \epsilon_{n,t},$$

where x_t is some proxy for expected excess returns, which is the CP factor in this case. I use the exact same procedure as in Cochrane and Piazzesi (2005) to construct the CP factor. In order to make my results comparable to the results of Campbell and Shiller (1991), I use McCulloch and Kwon (1993) data set over the period 1952:1 to 1991:2.

Table 2.1 reports the estimated regression coefficients $\hat{\gamma_n}$ and $\hat{\phi_n}$. The maturity of the short term bond is fixed at 1 month, and the long term bond maturity (n) varies from 2 months to 120 months (10 years). Panel A. of Table 2.1 reports estimated coefficients $\hat{\gamma_n}$ with standard errors proposed in Newey and West (1987)[1] correcting for heteroskedasticity and overlap in the equation errors. There is no proxy for the expected excess return term included in the regressions except for the constant term. The estimated coefficients are less than one but significantly positive when n is small. They become insignificant for intermediate terms, 1 through 5 years. At 10-year end, the coefficient is significant and greater than 1. It shows a different picture when CP factor is included as a proxy for the expected excess return. Panel B. of Table 2.1 reports the estimated coefficients when the CP factor is included. Over short horizon (less than a year), the coefficients stay virtually the same after the CP factor is introduced. At the 10-year end, the CP factor does not do much work either as the change in the estimated coefficient of the yield spread is small. Nevertheless, there are dramatic increases in the estimated coefficients of the yield spread starting from 1 year to 5 years. The coefficients become even significantly greater than 1 beyond 2 years. Moreover, Cochrane and Piazzesi (2005) show that the CP factor is positively correlated with bond risk premia. Therefore, I expect the coefficient in front of the CP factor to be negative according to equation (2.1), although I cannot say much about its magnitude. The results presented in Panel B. of Table 2.1 confirms the conjecture: the estimated coefficients of the CP factor are all negative across different long term bond maturities, and they are statistically significant when n is in between 1 year and 5 years.

I have a completely different pattern when I look at the long term yield change regression

[1] I use Newey-West correction with 18 lags for standard errors reported throughout Table 2.1 - 2.4. Because the construction of $s^*_{n,t}$ uses future information, the error term in the short-rate-change specification is a moving average of order $(n-1)$. I check the standard error reported in Table 2.1 using up to 72 lags, and the results are almost the same.

derived from equation (2.2). Table 2.2 reports the estimated regression coefficient $\hat{\beta}_n$ and $\hat{\psi}_n$ for various combinations of short term and long term maturities. Panel A. of Table 2.2 reports the estimated coefficients $\hat{\beta}_n$ when no proxy for the expected excess return is included. Panel B. of table 2.2 reports the same estimated coefficients as in Panel A. when the CP factor is included. Panel C. of table 2.2 reports the estimated coefficients in front of the CP factor. In order to see how the estimated coefficients of the normalized yield spread change differently after introducing the CP factor in contrast to earlier results for the short rate change regressions, let's fix the short term bond maturity at 1 month ($m = 1$). I compare the first row of Panel A. of Table 2.2 with the first row of Panel B. of Table 2.2. When there is no proxy for the expected excess return, the estimated coefficients of the normalized yield spread are generally negative. As I can see from the first row of Panel A, the coefficient tend to decrease with the long term maturity n. More interestingly, the coefficients remain negative when the CP factor is included, although they increase marginally beyond 2 years (see first row of Panel B. Table 2.2). This is in sharp contrast with the short rate change regression results where I start to observe significant improvements when the long term maturities are beyond 1 year. In addition to the variation of long term bond maturities, I also check the robustness of the pattern by looking at different short term bond maturities. Proceeding through other rows and columns of Panel A. and Panel B. in Table 2.2, it appears the pattern is quite robust. The effect from including the CP factor starts to show up when short term bond maturities are beyond 6 months. The coefficients turns to a level close to 1 when annual yield rate is considered as the short rate (See row $m = 12$ of Panel B. Table 2.2). Yet, at 10-year end, the coefficient remains negative. To show the robustness of the pattern across different time periods, Table 2.3 reports the long term yield change regression on different subsamples. The coefficients of the normalized yield spread reported in Panel A. are from regressions with no proxy for expected excess returns. Those reported in Panel B. comes from regressions with the CP factor. Short term bond maturity is fixed at 1 month, and each row represents different long term bond maturities. In most cases, there is little change in the estimated coefficients of normalized spread when the CP factor is included as a proxy for bond risk premia.

The above estimations suggest that the CP factor does not contribute much in capturing the bond expected excess return when the short term bond maturities are less than 1 year. On the other hand, the short term yield change regressions (Table 2.1) fix the short term bond maturity at 1 month. It is evident that the CP factor performs quite well when the long term bond maturities are beyond 1 year, as I see from the significant improvements in the estimated coefficients of yield spreads. However, one can not simply take the result from the short rate change regressions as an evidence indicating the CP factor is a good proxy for expected excess returns of long maturity bonds. To see this point, let's look at the expected excess return term in equation (2.1): $\left(\frac{1}{n}\right)\sum_{i=1}^{n}(r_{n+1-i,t+i} - y_{1,t+i-1})$. The short term bond maturity is 1 month. So the time unit in the expression is 1 month, and n represents the number of months for the long term bond maturity. For large n, I have

$$
\begin{aligned}
&\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{i=1}^{n}(r_{n+1-i,t+i}-y_{1,t+i-1})\\
&\quad=\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{i=1}^{n}r_{n+1-i,t+i}-\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{i=1}^{n}y_{1,t+i-1}\\
&\quad=\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{j=0}^{n/12}\left(\sum_{i=1}^{12}r_{n+1-(i+12j),t+(i+12j)}\right)-12y_{12,t+12j}\\
&\qquad-\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{j=0}^{n}\left[\left(\sum_{i=1}^{12}y_{1,t+(i+12j)-1}\right)-12y_{12,t+12j}\right]\\
&\quad=\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{j=1}^{n/12}r_{n-12j,t+12(j+1)}-12y_{12,t+12j}\\
&\qquad+\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{j=1}^{n/12}\sum_{i=1}^{12}\left(p_{12-i,t+12j+i}-p_{12-i+1,t+12j+i-1}-y_{1,t+(i+12j)-1}\right)\\
&\quad=\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{j=1}^{n/12}r_{n-12j,t+12(j+1)}-12y_{12,t+12j}\\
&\qquad+\left(\frac{1}{n}\right)\mathbb{E}_t\sum_{j=1}^{n/12}\sum_{i=1}^{12}r_{12-i+1,t+12j+i}-y_{1,t+(i+12j)-1}
\end{aligned}
$$

So I can rewrite the expected excess return term into the sum of two parts. The first part, $\mathcal{A}\equiv\mathbb{E}_t\sum_{j=1}^{n/12}r_{n-12j,t+12(j+1)}-12y_{12,t+12j}$, represents the expected excess return of long term bond over a 1-year bond yield[2]. The second part, $\mathcal{B}\equiv\mathbb{E}_t\sum_{j=1}^{n/12}\sum_{i=1}^{12}r_{12-i+1,t+12j+i}-y_{1,t+(i+12j)-1}$, represents the expected excess return of long term bond with maturities less than 1 year over a 1-month bond yield. Cochrane and Piazzesi (2005) show that the CP factor has substantial explanatory power for bond expected excess returns at the annual horizon. Therefore, for n beyond one year the CP factor performs quite well as a proxy for the expected excess return term in equation (2.1) because it explains term $\mathcal{A}$ very well. Together with the evidence from the long term yield change regressions, one might suspect that the CP factor explains term $\mathcal{B}$ rather poorly. As a consequence, the CP factor is a very noisy proxy of the expected excess return term in equation (2.1) whenever the variation of $\mathcal{B}$ dominates the variation of $\mathcal{A}$. It happens for small n as well as when n is very large.

[2]The time unit is 1 month, therefore $y_{12,t+12j}$ represents the monthly yield of a 1-year bond at time $t+12j$, and $12y_{12,t+12j}$ gives the annualized yield.

This also explains the pattern I find in Table 2.1 when the CP factor is included as a proxy for expected excess returns. When n is less than a year or at 10-year end, the estimated coefficients change rather moderately after the CP factor is included relative to cases where n ranges from 1 year to 5 years.

To further strengthen the results that the CP factor does a poor job explaining bond risk premia when I look at different maturities for short rate, I construct bond excess returns for various combinations of short term and long term maturities. Following the same practice as in Cochrane and Piazzesi (2005), I run the following restricted regression

$$RX_{t+1} = \lambda x_t + \epsilon_{t+1}$$

where RX_{t+1} denotes the excess return, x_t is the CP factor. Note that it is a restricted specification because there is no constant term. Cochrane and Piazzesi (2005) emphasizes that a single factor drives bond expected returns across all maturities, therefore the constant term should be excluded under the restricted model. Table 2.4 Panel A. reports the estimated coefficients $\hat{\lambda}$ at various short term and long term bond maturities. Panel B of Table 2.4 reports the corresponding R^2 values[3]. Panel A. of Table 2.4 shows that statistically, I cannot distinguish the coefficients from zero when both the short term bond maturity m and the long term bond maturity n are small. The coefficients become significantly positive when n is large or the short rate maturity is 1 year. Panel B. shows that the significant estimated coefficients do not lead to a high R^2. In Cochrane and Piazzesi (2005), they show that the single factor model for bond excess return is able to reach R^2 level about 30%, a level comparable to the very last row of Panel B. Nevertheless, the levels of R^2 reported in other rows of Panel B. are only about 5% on average, substantially below 20%. Some of them are even negative. The evidence indicates the CP factor does not capture much of the bond excess return movements when I consider different short term bond maturities.

There are several important messages from the above exercise. First, the results suggest that the CP factor does not capture bond risk premia across all maturities. Its performance is especially poor when the short rate maturity is small. By using the proposed latent-variable model, I am able to uncover the process of bond risk premia from the model. Thus, I can provide more direct evidence by looking at the co-movement of the expected excess return process with the CP factor process. Second, standard affine term structure model (ATSM) adopts a set of primitive factors and tries to explain the movement of the yield curve. These factors governs bond prices, yields, as well as risk premia. Therefore, if there is a factor captures bond risk premia at some short rate maturity, it should do so across all maturities, because the factor is priced in the market. The CP factor performs really well in explaining bond excess return when the short rate horizon is 1 year. Hence ATSM suggests that it should also explain bond excess returns at other maturities. Unfortunately, empirical results

[3]Constant terms are excluded from the regression, therefore R^2 can be negative sometimes. I use the same formula to compute R^2 as in Cochrane and Piazzesi (2005). It ensures R^2 is nondecreasing when more explanatory variables are included.

seem to suggest otherwise. Therefore I decide to take a more direct structural approach to study the dynamics of bond risk premia. Third, the latent-variable is built on equation (2.1). According to the short rate change regression results presented earlier, there are significant improvements on the estimated coefficients in front of yield spreads when a good proxy for the expected excess return term is included. Thus, it shows that the latent-variable model approach is promising to uncover the process of bond risk premia and that of the short rate change.

2.3 Data and Estimation

2.3.1 Data

I obtain treasury bond yields from two sources. Data from McCulloch and Kwon (1993) covers the period from 1952 : 1 to 1991 : 2. It includes monthly yield information from 1 to 18 months, then quarterly to 2 years. This is especially helpful to construct series of bond excess returns without any approximation for my baseline results, where I use 3-month yield as the short rate. The second data source is the Fama-Bliss data from CRSP. It contains the annual increment yields from 1 year to 5 years for the period of 1964 – 2008. To check the relationship of identified shocks with monetary policy shocks, I use the measures of monetary policy shocks from Romer and Romer (2004).

2.3.2 State Space Representation of Yield Spread

In this section, I will formulate the latent-variable model. From Campbell and Shiller (1991):

$$\begin{aligned} s_{nt} &\equiv y_{nt} - y_{1t} \\ &= \left(\frac{1}{n}\right) \mathbb{E}_t \left[\sum_{i=0}^{n-1} r_{n-i,t+1+i} - y_{1t} \right] \\ &= \left(\frac{1}{n}\right) \mathbb{E}_t \left[\sum_{i=1}^{n} [(y_{1,t+i-1} - y_{1t}) + (r_{n-i+1,t+i} - y_{1,t+i-1})] \right] \end{aligned}$$

$$s_{nt} = \left(\frac{1}{n}\right) \mathbb{E}_t \left[\sum_{i=1}^{n} [(n-i)\Delta y_{1,t+i} + (r_{n+1-i,t+i} - y_{1,t+i-1})] \right] \tag{2.3}$$

I can specify different processes for $\Delta y_{1,t+1}$ and $r_{m,t+1} - y_{1,t}, \forall m$, and derive state space representation from there. However, I have to specify too many parameters to capture conditional mean shocks, realization shocks, as well as correlation among them. The number of parameters is of order n^2, therefore I do not pursue in this direction.

Instead, let $r^x_{t+1} = \frac{1}{n-1} \sum_{i=2}^{n} (r_{i,t+1} - y_{1,t})$, i.e. the average excess return of holding bonds.

Let $\mathbb{E}_t[r^x_{t+1}] = \mu_t$, of which the dynamic I am interested in. I want to make the cross sectional properties of yield curve as flexible as possible, since I am focusing on the dynamic properties. Cochrane and Piazzesi (2005) and Cochrane (2008a) suggest that there is a single factor that drives the expected excess return across all maturities. Comply with their finding, I make the following assumption:

$$\mathbb{E}_t[r_{i,t+1} - y_{1,t}] = c_i + b_i x_t,$$

where x_t is the factor that drives the expected excess return. Then it yields:

$$\mu_t = \frac{1}{n-1}\sum_{i=2}^{n}(c_i + b_i x_t) \equiv \bar{c} + \bar{b}x_t,$$

where $\bar{c} = \frac{1}{n-1}\sum_{i=2}^{n} c_i$ and $\bar{b} = \frac{1}{n-1}\sum_{i=2}^{n} b_i$. It follows:

$$\mathbb{E}_t[r_{i,t+1} - y_{1,t}] = c_i - \frac{b_i}{\bar{b}}\bar{c} + \frac{b_i}{\bar{b}}\mu_t \equiv \tilde{c}_i + f(i)\mu_t,$$

where $\tilde{c}_i = c_i - \frac{b_i}{\bar{b}}\bar{c}$, and $f(i) = \frac{b_i}{\bar{b}}$. Note that $\sum_{i=2}^{n}\tilde{c}_i = 0$ and $\sum_{i=2}^{n} f(i) = n-1$. Now equation (2.3) yields:

$$\begin{aligned} s_{nt} &= \frac{1}{n}\sum_{i=1}^{n}(n-i)\mathbb{E}_t[\Delta y_{1,t+i}] + \frac{1}{n}\sum_{i=1}^{n-1}\mathbb{E}_t[r_{n+1-i,t+i} - y_{1,t+i-1}], \\ &= \frac{1}{n}\sum_{i=1}^{n-1}(n-i)\mathbb{E}_t[\Delta y_{1,t+i}] + \frac{1}{n}\sum_{i=1}^{n-1} f(n+1-i)\mathbb{E}_t[r^x_{t+i}]. \end{aligned} \tag{2.4}$$

So the state space representation is built on equation (2.4). In order to estimate the model later, I need to know $f(.)$. Fortunately, this is very easy to obtain because

$$f(i) = \frac{b_i}{\bar{b}} = \frac{Cov(r_{i,t+1} - y_{1,t}, r^x_{t+1})}{Var(r^x_{t+1})}. \tag{2.5}$$

A simple regression will get the job done. Now assume the following processes for expected change in short rate and expected average excess return of bond:

$$g_{t+1} = \gamma_0 + \gamma_1(g_t - \gamma_0) + \epsilon^g_{t+1}, \tag{2.6}$$

$$\mu_{t+1} = \delta_0 + \delta_1(\mu_t - \delta_0) + \epsilon^\mu_{t+1}, \tag{2.7}$$

where,

$$\begin{aligned} \mu_t &\equiv \mathbb{E}_t[r^x_{t+1}] \\ g_t &\equiv \mathbb{E}_t[\Delta y_{1,t+1}] \end{aligned}$$

The realized change of short rate is equal to the expected change of short rate plus an orthogonal shock:

$$\Delta y_{1,t+1} = g_t + \epsilon^y_{t+1} \tag{2.8}$$

I model the time series processes for both the expected excess return and the expected short rate change as AR(1) processes. One might be uncomfortable making such assumption for the expected short rate change, because it implies the process for the expected short rate an I(1) in levels. There are two reasons why one might prefer modeling process for the expected short rate change instead of modeling in levels. First, I know that short rates are highly persistent in the data. Ang and Piazzesi (2003) find an auto correlation of 0.972 for 1 month T-bill yield, with increasing autocorrelation at longer maturities. Thus, modeling the short rate in levels might generate an unstable system, which is unpleasant for the forecasting purpose. Second, Piazzesi (2005) documents the fact that federal fund rate tends to move in the same direction because of the policy inertia. The short rate in the bond market moves closely with the federal fund rate, therefore the empirical fact is more consistent with an AR(1) process for the expected short rate change than a stationary process for the short rate in levels. Modeling the expected short rate changes this way does, however, imply an unstationary process for the stochastic discount factor as in the standard affine term structure model. Therefore, I also consider modeling the short rate itself to have a autoregressive component, an AR(1). Now the process for the short rate is stationary, and it is also consistent with the specification of standard affine term structure model. It turns out that the expected short rate change follows an ARMA(1,1) process as oppose to an AR(1) process specified before. To see this, let $f_{t-1} = \mathbb{E}_{t-1}[y_{1,t}]$, which represents the expected period t short rate at period $t-1$. Then I can write the short rate at period t as

$$y_{1,t} = f_{t-1} + v_t.$$

The expected short rate follows an AR(1) process:

$$f_t = \alpha_0 + \alpha_1(f_{t-1} - \alpha_0) + \xi_t.$$

Now I can write the expected short rate change as

$$\mathbb{E}_t[\Delta y_{1,t+1}] = f_t - f_{t-1} - v_t.$$

I know that

$$f_t = f_{t-1} = (\alpha_1 - 1)(f_{t-1} - \alpha_0) + \xi_t,$$

it yields

$$\mathbb{E}_t[\Delta y_{1,t+1}] = (\alpha_1 - 1)(f_{t-1} - \alpha_0) + \xi_t - v_t.$$

Since f_t follows an AR(1) process, $(\alpha_1 - 1)(f_{t-1} - \alpha_0)$ also follows an AR(1) process. Hence $\mathbb{E}_t[\Delta y_{1,t+1}]$ is a sum of an AR(1) and a white noise term. This yields an ARMA(1,1) process for the expected short rate change. Following the same notation as before $g_t \equiv \mathbb{E}_t[\Delta y_{1,t+1}]$, I can write

$$g_{t+1} = \gamma_0 + \gamma_1(g_t - \gamma_0) + \rho\epsilon_t^g + \epsilon_{t+1}^g. \tag{2.9}$$

Note that if $\rho = 0$, I go back the same specification as in assumption (2.6). So equation (2.9) is a more general assumption. Furthermore, it makes easier for me to compare the estimation result across the two specifications. This is also another advantage of modeling expected short rate change, since the expected short rate change is a stationary process either the short rate is stationary or it follows an I(1). If I model the short rate in levels, then the system is not stable if the short rate itself is not stationary, which it makes it impossible to compare across different specifications.

Iterate equation (2.4), using the AR(1) assumption for the expected excess return and AR(1, 1) assumption for the expected short rate change (2.7) - (2.9), it follows that:

$$s_{nt} = A + B(g_t - \gamma_0) + C(\mu_t - \delta_0) + D\epsilon_t^g, \tag{2.10}$$

where

$$\begin{aligned}
A &= \frac{n-1}{2}\gamma_0 + \frac{\delta_0}{n}\sum_{i=1}^{n-1} f(n+1-i) = \frac{n-1}{2}\gamma_0 + \delta_0\frac{n-1}{n}, \\
B &= \frac{1}{n}\sum_{i=1}^{n-1}(n-i)\gamma_1^i, \\
C &= \frac{1}{n}\sum_{i=1}^{n-1} f(n-i+1)\delta_1^i, \\
D &= \frac{1}{n}\sum_{i=1}^{n-1} \rho(n-i)\gamma_1^{i-1} = \frac{\rho B}{\gamma_1}.
\end{aligned}$$

There are three shocks in the model: shocks to expected change of short rate (ϵ_{t+1}^g), shocks to expected average excess return (ϵ_{t+1}^μ), and shocks to realized change of short rate (ϵ_{t+1}^y). They have zero mean, covariance matrix:

$$\Sigma = \begin{pmatrix} \sigma_g^2 & \sigma_{g\mu} & \sigma_{gy} \\ \sigma_{g\mu} & \sigma_\mu^2 & \sigma_{\mu y} \\ \sigma_{gy} & \sigma_{\mu y} & \sigma_y^2 \end{pmatrix}$$

There are two latent variables in this model, μ_t and g_t. One follows an AR(1) process, and the other follows an ARMA(1, 1) process. The de-meaned state variables are:

$$\begin{aligned}\hat{\mu}_t &= \mu_t - \delta_0,\\ \hat{g}_t &= g_t - \gamma_0.\end{aligned}$$

Transition equations:

$$\begin{aligned}\hat{g}_{t+1} &= \gamma_1 \hat{g}_t + \rho\epsilon_t^g + \epsilon_{t+1}^g,\\ \hat{\mu}_{t+1} &= \delta_1 \hat{\mu}_t + \epsilon_{t+1}^{\mu}.\end{aligned}$$

Two measurement equations:

$$\begin{aligned}\Delta y_{1,t+1} &= \gamma_0 + \hat{g}_t + \epsilon_{t+1}^y,\\ s_{nt} &= A + B\hat{g}_t + C\hat{\mu}_t + D\epsilon_t^g.\end{aligned}$$

Note that one of the measurement equation does not contain any unrealized error term, therefore I can use that to substitute out one transition equation. In this case, I will substitute out the de-meaned return equation. Now I am left with one transition equation and two measurement equations:

$$\hat{g}_{t+1} = \gamma_1 \hat{g}_t + \epsilon_{t+1}^g \tag{2.11}$$

$$\Delta y_{1,t+1} = \gamma_0 + \hat{g}_t + \epsilon_{t+1}^y \tag{2.12}$$

$$s_{n,t+1} = A(1-\delta_1) + B(\gamma_1 - \delta_1)\hat{g}_t + \delta_1 s_{nt} + (\rho B - \delta_1 D)\epsilon_t^g + (B+D)\epsilon_{t+1}^g + C\epsilon_{t+1}^{\mu} \tag{2.13}$$

This completes the state space representation of the yield spread.

2.3.3 Kalman filter

Now I can formulate the model in the standard state-space form. Define a state vector:

$$X_t = \begin{bmatrix} \hat{g}_{t-1} \\ \epsilon_t^g \\ \epsilon_t^y \\ \epsilon_t^{\mu} \\ \epsilon_{t-1}^g \end{bmatrix},$$

which satisfies:

$$X_{t+1} = FX_t + \Gamma\epsilon_{t+1}^X,$$

with

$$F = \begin{bmatrix} \gamma_1 & 1 & 0 & 0 & \rho \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix}, \qquad \Gamma = \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix},$$

and where

$$\epsilon_t^X = \begin{bmatrix} \epsilon_t^g \\ \epsilon_t^y \\ \epsilon_t^\mu \end{bmatrix} \quad \sim \quad \mathcal{N}\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \Sigma \right).$$

The measurement equation, which has the observables $Y_t = (\Delta y_{1,t}, s_{n,t})^T$, is:

$$Y_t = M_0 + M_1 Y_{t-1} + M_2 X_t,$$

with

$$\begin{aligned} M_0 &= \begin{bmatrix} \gamma_0 \\ A(1-\delta_1) \end{bmatrix}, \\ M_1 &= \begin{bmatrix} 0 & 0 \\ 0 & \delta_1 \end{bmatrix}, \\ M_2 &= \begin{bmatrix} 1 & 0 & 1 & 0 & 0 \\ B(\gamma_1 - \delta_1) & B + D & 0 & C & \rho B - \delta_1 D \end{bmatrix}. \end{aligned}$$

The Kalman procedure is given by:

$$\begin{aligned} X_{0|0} &= E[X_0] = 0_{4\times 1}, \\ P_{0|0} &= E[X_t X_t'], \\ X_{t|t-1} &= F X_{t-1|t-1}, \\ P_{t|t-1} &= F P_{t-1|t-1} F' + \Gamma \Sigma \Gamma', \\ \eta_t &= Y_t - M_0 - M_1 Y_{t-1} - M_2 X_{t|t-1}, \\ S_t &= M_2 P_{t|t-1} M_2', \\ K_t &= P_{t|t-1} M_2' S_t^{-1}, \\ X_{t|t} &= X_{t|t-1} + K_t \eta_t, \\ P_{t|t} &= (I - K_t M_2) P_{t|t-1}. \end{aligned}$$

The log likelihood is

$$\mathcal{L} = -\sum_{t=1}^{T} \log(det(S_t)) - \sum_{t=1}^{T} \eta_t' S_t^{-1} \eta_t.$$

The covariance matrix of the shocks is:

$$\Sigma \equiv \begin{bmatrix} \sigma_g^2 & \sigma_{gy} & \sigma_{g\mu} \\ & \sigma_y^2 & \sigma_{y\mu} \\ & & \sigma_\mu^2 \end{bmatrix}.$$

I maximize the log likelihood over the parameters:

$$\Theta \equiv (\gamma_0, \delta_0, \gamma_1, \delta_1, \sigma_g, \sigma_y, \sigma_\mu, \rho_{gy}, \rho_{g\mu}, \rho_{y\mu}, \rho).$$

2.3.4 Identification

In the model, all but one parameters in the covariance matrix are identified. I restrict the correlation between shocks to the expected short rate change (ϵ_{t+1}^g) and shocks to the unexpected short rate change (ϵ_{t+1}^y) to be zero.

2.3.5 Estimation

I propose a two-step consistent estimation procedure. In the first step, I obtain an estimate of function $f(.)$ that captures the cross sectional relationships of the expected excess return among bonds with different maturities. As suggested in equation (2.5), this can be simply done via standard OLS regression. In the second step, I take the estimated function $\hat{f}(.)$ from the first step as given, then construct the log likelihood function using Kalman filter technique, and estimate the parameters of the model by means of maximum likelihood. I am only using information about the short rate change and the yield spread at the second step. It is important to reduce the number of parameters to be estimated at this stage for both identification and efficiency concerns. Because the model has many parameters, I adopt a Quasi-Bayesian estimation to optimize the log likelihood function. More specifically, I use Markov chain Monte Carlo (MCMC) methods to ensure the estimates obtained reach the global maximum of the log likelihood function.

2.4 Results

2.4.1 From the McCulloch and Kwon Data

Table 2.5 presents the estimation results. The estimates correspond to the parameters specified in equation (2.11) - (2.13) where I use the 3-month yield as the short rate and 2-year yield as the long term rate to compute the yield spread. The reason that I choose the 2-year yield as the long term yield is that McCulloch and Kwon's data set contains bond yields with maturity frequency finer than or equal to one quarter for yields with maturity less than 2 years. Beyond two years, the yields are semiannually to three years, then annually to 35 years, and finally a five year jump to 40 years. Thus the 2-years bond is the bond with longest maturity bond which allows me to compute the bond excess return without any approximation. It is needed for the first step estimation. Results of both specifications of the process of the expected short rate change are presented in Table 2.5 to check if results are sensitive to the model specification.

Under the AR(1) specification of the expected short rate change, the unconditional expected short rate change has an estimate $\delta_0 = 0.03\%$, a level both statistically and economically insignificant. The unconditional mean of average expected log excess return is $\gamma_0 = 0.48\%$ under AR(1) specification, and $\gamma_0 = 0.56\%$ under ARMA(1,1) specification. Furthermore, I find expected excess returns to be highly persistent, with an annual persistence coefficients $\gamma_1 = 0.87$ under both AR(1) and ARMA(1,1) specification. The expected short rate change also has a persistent component, $\delta_1 = 0.20$, which is less than the estimated persistence of expected excess returns. The estimates of correlation between shocks to expected short rate change and shocks to expected excess return are small and negative under both specifications: -0.076 under AR(1) and -0.062 under ARMA(1,1). However, there is a significant negative correlation between shocks to unexpected short rate changes and shocks to expected excess returns, $\rho_{y\mu} = -0.66$ under AR(1) and $\rho_{y\mu} = -0.65$ under ARMA(1,1). Finally the moving average component of the expected short rate change under ARMA(1,1) specification does not have a significant estimate.

Panel B. of Table 2.5 reports the implied present value parameters. It helps me understand the variance of the yield spread. Given the estimate of D and ρ are very small, I will set them to be zero for the moment. So I will use the estimates from AR(1) specification for the variance decomposition analysis, although the result is very much similar under the ARMA(1,1) specification. The variance decomposition of the yield spread is given by

$$\begin{aligned} var(s_{n,t}) &= B^2 var(g_t) + C^2 var(\mu_t) + 2BC cov(\mu_t, g_t) \\ &= \frac{B^2\sigma_g^2}{1-\delta_1^2} + \frac{C^2\sigma_\mu^2}{1-\gamma_1^2} + \frac{2BC\sigma_{g\mu}}{1-\delta_1\gamma_1} \end{aligned} \tag{2.14}$$

The first term, $B^2 var(g_t)$, represents the variation in the yield spread due to the expected short rate change variation. The second term, $C^2 var(\mu_t)$, measures the variation in the yield spread due to the expected excess return variation. The third term measure the covariation between these components. Table 2.6 summarizes the results, where the numbers are normalized so that they sum up to 100%. I find that most of the variation in the yield spread comes from the expected excess return variation.

Similar to van Binsbergen and Koijen (2010) and Harvey (1990), I compute the R^2 values for excess returns and short rate changes from the state-space model as

$$R^2_{er} = 1 - \frac{v\hat{a}r(r_{t+1} - \mu^F_t)}{v\hat{a}r(r_t)},$$
$$R^2_{cs} = 1 - \frac{v\hat{a}r(\Delta y_{1,t+1} - g^F_t)}{v\hat{a}r(\Delta y_{1,t+1})},$$

where $v\hat{a}r$ is the sample variance, μ^F_t is the filtered series for expected excess returns (μ_t), and g^F_t is the filtered series for expected short rate changes g_t. Panel C. of Table 2.5 reports the statistics. The R^2 value for expected excess returns is equal to 12.09% under AR(1) 12.15% under ARMA(1,1), and that for expected short rate change reaches a surprising level of 78.96% and 81.48% respectively under the two specifications. To give a visual perspective, Figure 2.1 and Figure 2.2 plots the series of average excess return, short rate changes, and their corresponding filtered series from the state-space model.

2.4.2 Comparing with results using the Fama-Bliss Data

I repeat the same exercise on the Fama Bliss data set to estimate the state-space model of the yield spread, where the spread is defined as the 5-year bond yield minus the 1-year bond yield. The data set covers the period from 1964 to 2008. The results are shown in Table 2.7. First, I find that the different specifications of the short rate change give the similar estimates of the parameters. I cannot statistically reject the AR(1) model over the ARMA(1,1) model, similar to what I find using the McCulloch and Kwon data. The unconditional expected change of short rate has an estimate $\delta_0 = 0.02\%$, and it is statistically insignificant. The estimate of the unconditional bond expected excess return ($\gamma_0 = 0.20\%$). Although it is statistically significant, it is much lower than the sample mean of the average excess return, which is about 0.84%. It is also lower than the estimated unconditional bond expected excess return (about 0.55%) when using 3-month yield as the short rate from the MK data. Once again, the state space model detects persistent components in both expected short rate change and bond risk premia. In the ARMA(1,1) specification, the autoregressive coefficient δ_1 has an estimate of 0.23, a level similar to the estimate using the MK data. In contrast, the expected excess return becomes more persistent when the underlying short rate is 1-year bond yield. In both AR(1) and ARMA(1,1) model, the estimate γ_1 is highly significant and exceeds 0.96, which is about more than 10% higher than the estimate obtained using the MK data where the underlying short rate is the 3-month bond yield. Recall the fact that the forward rates are very persistent in the data, this makes the R^2 obtained in Cochrane and Piazzesi (2005) less reliable. The correlation between shocks to the expected short rate change and shocks to bond risk premia raises to -0.14. However, the shocks to the unexpected short rate change are more correlated with the shocks to bond risk premia. The estimate of the correlation is -0.7. This pattern is very similar to what I observe in the MK data.

Panel B. of Table 2.7 reports the present value parameters. I follow the same exercise as before to decompose the variance of the yield spread under the AR(1) specification. Similar to the finding using the MK data, I find that most of the variation comes from the expected excess return variation (See Table 2.6). Finally Panel C. of Table 2.7 reports the R^2 to check the predictability of the model. R^2 of the excess returns is about 12%, about the same level as obtained in the MK data set. But this value is significant lower than the R^2 value using the CP factor in Cochrane and Piazzesi (2005). R^2 value for the short rate changes drops significantly to 35% under the ARMA(1,1) specification from about 80% when using 3-month yield as the short rate, which suggests the predictability of the short rate change falls as the maturity of the short rate increases. Figure 2.3 and Figure 2.4 plots the series of average expected excess returns, short rate changes, and their corresponding filtered series from the state-space model.

To sum up, I find that the following patterns of the estimation are robust across the two data sets:

- Both expected short rate changes and bond expected excess returns have persistent components, and the expected excess returns are more persistent than the expected short rate changes.

- There is very little co-movement between shocks to the expected short rate change and shocks to bond expected returns.

- Shocks to unexpected short rate changes are highly correlated with the shocks to the bond expected excess returns.

- Most of the variation of the yield spread comes from the variation of the bond expected excess return.

However, the persistency of the bond expected excess return raises when I use short rates with longer maturity. In the case of Fama-Bliss data set, the estimated autoregressive coefficient of the bond expected excess return is more than 0.96.

2.5 Bond Risk Premium and Monetary Policy

In this section, I explore the source of the bond risk premium. More specifically, I want to understand what is driving the time-varying bond risk premia. In a standard endowment economy model, bonds generally carry a negative risk premium. In a bad state, agents want to save more to smooth their consumptions, which in turn drives up the price of bonds. This makes bonds a hedge instead of a risky asset. In order to explain the term premia in the bond market, people usually focus on the inflation risk, for instance, Piazzesi and Schneider (2006) and Bansal and Shaliastovich (2009). The idea is that inflation rises at those states that consumption growth is low. Therefore the inflation erodes the value of nominal bonds in those states and makes nominal bonds risky. The uncertainty of future inflation should be a key factor driving the time varying risk premia. Since the inflation is mainly a monetary phenomenon, monetary policy shocks should be closely related to the term permia.

From the estimation results, I learned that there is a significant negative correlation between shocks to unexpected short rate changes and shocks to bond average expected excess returns. Such correlation is important to understand the source of the time variation in the bond expected excess returns. To explore these shocks, I first treat the identified shock to unexpected short rate changes from the state-space model as factor and look at the loading of the shock across different maturities (3 month to 5 years for the MK data, 1 year to 5 year for the FB data). Figure 2.5 presents the results for both the MK data and the FB data. I see the shock to the unexpected short rate change most affects the short term end of the yield curve. Its loading diminishes as the maturity increases, even turns negative at the very long term end (only for the MK data). The feature mimics the impact of the monetary policy shocks on the yield curve (see Cochrane (2008a)). Therefore, the results suggest that the monetary policy plays an important role in explaining the time variation of bond risk premia. When the Federal Reserve Bank cut the interest rate unexpectedly, it raises the uncertainty of the future inflation. As a consequence, investors demand a higher premium to hold a long term bond. To provide more direct evidence of the link between identified shocks to unexpected short rate change from the state-space model and the monetary policy shocks, I compare the identified shock series with the monetary shock measure of Romer and Romer (2004). The measure from Romer and Romer (2004) covers the period from March 1969 to December 1996. The overlapping period with McCulloch and Kwon (1993) is from March 1969 to November 1990. I find that the correlation between the two series is 0.38. For the Fama-Bliss data set, I can look at the whole period from Match 1969 to December 1996. The correlation is even higher, 0.44. Figure 2.6 and Figure 2.7 show the plots of series of monetary shocks and identified shocks to unexpected short rate change for both the MK data and the FB data. I see that the two series are closely related in both cases.

2.6 Conclusion

In this chaper, I study the joint dynamics of the short rate change and bond risk premia. I start with a Campbell and Shiller (1991) present-value model, and demonstrate that the CP factor should not be treated as a factor capturing bond risk premia across all maturities. It does not help predict bond excess returns when I use yields with maturity less than 1 year as the short rate. This evidence suggests that the dynamic of the bond risk premia may be different under different underlying short rate. I assume that conditional short rate changes and conditional average bond expected returns are latent, following an exogenously specified ARMA model. I combine this model with the Campbell and Shiller (1991) present-value model to obtained the implied dynamics of the yield spread, and use Kalman filter technique to uncover the latent variables. The filtered series are good predictors for bond excess returns and short rate changes.

By comparing the estimation results between two different data sets, I look at how the dynamics of the bond risk premia changes when considering different underlying short rates. I find that the persistency of the bond risk premia increases as the maturity of the underlying short rate increases. Using the Fama-Bliss data set, I find the autoregressive coefficient has an estimate over 0.96 under both AR(1) and ARMA(1,1) specifications of the short rate change dynamic, while the coefficient estimate is only 0.87 when the underlying short rate is 3-month treasury yield. Together with the facts that the forward rates are very persistent in Fama-Bliss data set and the CP factor performs poorly in predicting excess returns for short rates with maturity less than a year. I suspect the difference in the persistence of the bond risk premia is responsible for the poor performance of the CP factor when the maturity of the short rate is less than one year.

Furthermore, I find no discernible co-movement between the expected change in the short rate and the bond risk premium using the McCulloch and Kwon (1993) data. The co-movement is still small when I use the Fama-Bliss data set. This evidence counters the hypothesis that there is a hidden factor that is important in predicting future bond excess returns (see Duffee (2009)). Rather, I find that the unexpected short rate change shock moves closely with the bond risk premia shock. I then use the monetary policy shock measure from Romer and Romer (2004), and show that the monetary policy plays an important role in explaining the time variation of the bond risk premia, which can be used as an evidence that the bond risk premia come from the future inflation uncertainty.

Table 2.1 Regression of Short Rate Change on Yield Spread

	n = 2	n = 3	n = 6	n = 12	n = 24	n = 36	n = 48	n = 60	n = 120
Panel A. No Proxy for Expected Excess Return									
Spread	0.502***	0.467***	0.320**	0.272	0.363	0.401	0.443	0.511	1.402***
	(0.104)	(0.145)	(0.145)	(0.177)	(0.248)	(0.299)	(0.345)	(0.357)	(0.169)
N	469	468	465	459	447	435	423	411	351
R-squared	0.109	0.0854	0.0329	0.0244	0.0401	0.0499	0.0573	0.0786	0.691
Panel B. CP facor as Proxy for Expected Excess Return									
Spread	0.506***	0.491***	0.385***	0.510***	1.163***	1.435***	1.489***	1.495***	1.483***
	(0.0972)	(0.123)	(0.122)	(0.168)	(0.236)	(0.258)	(0.302)	(0.324)	(0.226)
CP factor	-0.00385	-0.0177	-0.0431	-0.142**	-0.468***	-0.669***	-0.718***	-0.748***	-0.0879
	(0.0127)	(0.0200)	(0.0394)	(0.0629)	(0.109)	(0.130)	(0.155)	(0.185)	(0.0933)
N	469	468	465	459	447	435	423	411	351
R-squared	0.109	0.0899	0.0425	0.0716	0.224	0.301	0.300	0.327	0.695

Long term bond maturities are measured in months. Short term bond maturity is fixed at 1 month. Panel A reports the estimated regression coefficient of yield spread $s_{n,t}$, when there is no control for the expected excess return. Panel B reports the estimated coefficients for both yield spread and CP factor when CP factor is included as a proxy for expected excess returns. The Newey-West standard errors are reported in parentheses. The constant term is included in all regressions, but not reported. The underlying data are monthly zero-coupon bond yields over the period 1952:1 to 1991:2 from McCulloch and Kwon (1993).

Table 2.2 Regression of Long Term Yield Change on Normalized Spread

	n = 2	n = 3	n = 4	n = 6	n = 9	n = 12	n = 24	n = 36	n = 48	n = 60	n = 120
Panel A. No Proxy for Expected Excess Return											
m = 1	0.00328	-0.145	-0.346	-0.835*	-0.915	-1.029	-1.448	-1.890*	-2.264*	-2.613**	-4.220**
	(0.208)	(0.360)	(0.486)	(0.485)	(0.578)	(0.652)	(0.915)	(1.046)	(1.188)	(1.299)	(1.762)
m = 2		-0.305	-0.553	-1.124***	-1.551***	-1.325**	-1.665**	-1.937**	-2.306**	-2.621**	-4.068***
		(0.367)	(0.452)	(0.397)	(0.516)	(0.533)	(0.745)	(0.883)	(1.026)	(1.124)	(1.496)
m = 3			-0.406	-1.151***	-1.465***	-1.728***	-1.471**	-1.708**	-1.973**	-2.237**	-3.693***
			(0.296)	(0.368)	(0.463)	(0.510)	(0.629)	(0.743)	(0.865)	(0.958)	(1.315)
m = 4				-1.064***	-1.285***	-1.551***	-1.259**	-1.465**	-1.706**	-1.969**	-3.316***
				(0.344)	(0.361)	(0.421)	(0.530)	(0.644)	(0.748)	(0.844)	(1.256)
m = 6					-0.534	-0.814*	-0.718	-0.983	-1.210*	-1.462*	-2.629*
					(0.416)	(0.486)	(0.502)	(0.599)	(0.708)	(0.832)	(1.376)
m = 12							-0.822	-1.134	-1.426	-1.680	-2.607
							(0.629)	(0.753)	(0.876)	(1.029)	(1.652)
Panel B. CP factor as Proxy for Expected Excess Return											
m = 1	0.0113	-0.114	-0.307	-0.870*	-1.119*	-1.346*	-1.530	-1.188	-1.179	-1.804	-3.682*
	(0.194)	(0.326)	(0.443)	(0.471)	(0.601)	(0.687)	(0.995)	(1.241)	(1.470)	(1.593)	(1.948)
m = 2		-0.212	-0.445	-1.145***	-1.643***	-1.707***	-1.927**	-1.443	-1.370	-1.677	-2.828*
		(0.305)	(0.387)	(0.424)	(0.624)	(0.647)	(0.785)	(0.956)	(1.136)	(1.216)	(1.530)
m = 3			-0.258	-1.102**	-1.441**	-1.678**	-1.343*	-0.817	-0.642	-0.896	-2.105
			(0.242)	(0.447)	(0.604)	(0.649)	(0.706)	(0.815)	(0.970)	(1.049)	(1.386)
m = 4				-0.971**	-1.205**	-1.422***	-0.897	-0.386	-0.250	-0.547	-1.679
				(0.431)	(0.479)	(0.512)	(0.641)	(0.763)	(0.908)	(1.006)	(1.483)
m = 6					-0.118	-0.218	0.331	0.647	0.705	0.356	-0.705
					(0.472)	(0.576)	(0.670)	(0.836)	(0.979)	(1.092)	(1.641)
m = 12							1.420**	1.276	0.966	0.587	-0.207
							(0.665)	(0.890)	(0.965)	(1.079)	(1.476)
Panel C. Regression Coefficients of CP factor											
...											

Table 2.2 Regression of Long Term Yield Change on Normalized Spread

	n = 2	n = 3	n = 4	n = 6	n = 9	n = 12	n = 24	n = 36	n = 48	n = 60	n = 120
...											
Panel C. Regression Coefficients of CP factor											
m = 1	-0.008	-0.012	-0.009	0.005	0.017	0.017	0.002	-0.014	-0.017	-0.011	-0.005
	(0.025)	(0.023)	(0.021)	(0.020)	(0.020)	(0.019)	(0.016)	(0.014)	(0.014)	(0.012)	(0.009)
m = 2		-0.034	-0.029	0.004	0.012	0.037	0.013	-0.018	-0.029	-0.025	-0.021
		(0.034)	(0.031)	(0.040)	(0.042)	(0.040)	(0.032)	(0.027)	(0.025)	(0.022)	(0.018)
m = 3			-0.055	-0.015	-0.005	-0.007	-0.009	-0.048	-0.060*	-0.053	-0.041
			(0.051)	(0.056)	(0.058)	(0.057)	(0.047)	(0.040)	(0.036)	(0.033)	(0.027)
m = 4				-0.040	-0.020	-0.022	-0.033	-0.076	-0.085*	-0.074*	-0.056
				(0.069)	(0.069)	(0.068)	(0.063)	(0.054)	(0.049)	(0.044)	(0.036)
m = 6					-0.128	-0.135	-0.141*	-0.170**	-0.169**	-0.14**	-0.10**
					(0.087)	(0.089)	(0.082)	(0.073)	(0.067)	(0.061)	(0.049)
m = 12							-0.551***	-0.460***	-0.392***	-0.339***	-0.248***
							(0.123)	(0.116)	(0.101)	(0.093)	(0.074)

Bond maturities are measured in months. n represents the maturities for long term bonds, m represents the maturities for short term bonds. Panel A. reports the estimated regression coefficient of the normalized spread $\frac{s_{n,t}}{n-m}$, when there is no control for the expected excess return. Panel B. reports the estimated regression coefficients of the normalized spread, when CP factor is included as a proxy for expected excess returns. Panel C. reports the estimated coefficients of the CP factor when it is included. The Newey-West standard errors are reported in parentheses. The constant term is included in all regressions, but not reported. The underlying data are monthly zero-coupon bond yields over the period 1952:1 to 1991:2 from McCulloch and Kwon (1993).

Table 2.3 Regression of Long Term Yield Change on Nomalized Spread: Subsamples

	Panel A. No Proxy for Expected Excess Return						Panel B. CP factor as Proxy for Expected Excess Return					
	1952-91	1952-78	1952-59	1960-69	1970-78	1979 - 91	1952-91	1952-78	1952-59	1960-69	1970-78	1979-91
n = 2	0.00328	-0.261**	-0.266**	-0.0952	-0.414	0.277	0.0113	-0.306***	-0.280**	-0.0630	-0.592*	0.281
	(0.208)	(0.114)	(0.107)	(0.226)	(0.381)	(0.295)	(0.194)	(0.108)	(0.135)	(0.231)	(0.321)	(0.312)
n = 3	-0.145	-0.471***	-0.195	-0.387	-0.849***	0.115	-0.114	-0.558***	-0.254	-0.416	-1.088**	0.136
	(0.360)	(0.135)	(0.133)	(0.368)	(0.310)	(0.480)	(0.326)	(0.178)	(0.178)	(0.338)	(0.424)	(0.446)
n = 4	-0.346	-0.519***	-0.106	-0.490	-0.867**	-0.210	-0.307	-0.644***	-0.230	-0.524*	-1.149***	-0.125
	(0.486)	(0.164)	(0.168)	(0.352)	(0.427)	(0.676)	(0.443)	(0.199)	(0.235)	(0.298)	(0.384)	(0.607)
n = 6	-0.835*	-0.537**	0.113	-0.564*	-0.981*	-0.957	-0.870*	-0.719**	-0.162	-0.616**	-1.276**	-0.923
	(0.485)	(0.233)	(0.226)	(0.335)	(0.585)	(0.682)	(0.471)	(0.279)	(0.334)	(0.271)	(0.551)	(0.673)
n = 9	-0.915	-0.400	0.584*	-0.604	-0.915	-1.139	-1.119*	-0.773	-0.0179	-0.839	-1.302	-1.243
	(0.578)	(0.335)	(0.321)	(0.557)	(0.554)	(0.833)	(0.601)	(0.522)	(0.484)	(0.693)	(1.049)	(0.885)
n = 12	-1.029	-0.576	0.760*	-1.039	-0.983	-1.166	-1.346*	-1.120	-0.181	-1.343	-1.523	-1.304
	(0.652)	(0.406)	(0.432)	(0.813)	(0.604)	(0.936)	(0.687)	(0.701)	(0.630)	(1.024)	(1.444)	(1.025)
n = 24	-1.448	-0.960*	1.781	-2.899**	-0.930	-1.614	-1.530	-1.094	0.209	-3.140*	-0.105	-1.589
	(0.915)	(0.578)	(1.181)	(1.379)	(0.741)	(1.290)	(0.995)	(0.828)	(1.115)	(1.720)	(1.859)	(1.531)
n = 36	-1.890*	-1.171	3.004	-3.832**	-1.185	-2.199	-1.188	0.122	2.439	-3.566	2.370	-1.654
	(1.046)	(0.741)	(2.028)	(1.830)	(0.825)	(1.434)	(1.241)	(1.159)	(1.675)	(2.199)	(2.285)	(1.848)
n = 48	-2.264*	-1.231	3.801	-4.333*	-1.235	-2.762*	-1.179	0.0863	3.311	-3.973	2.610	-1.479
	(1.188)	(0.872)	(2.731)	(2.249)	(0.914)	(1.631)	(1.470)	(1.369)	(2.495)	(2.567)	(2.317)	(2.309)
n = 60	-2.613**	-1.352	4.160	-4.870*	-1.228	-3.240*	-1.804	-0.728	3.155	-4.696*	1.554	-1.961
	(1.299)	(0.988)	(3.325)	(2.529)	(1.023)	(1.779)	(1.593)	(1.443)	(3.123)	(2.744)	(2.285)	(2.634)
n = 120	-4.220**	-2.217*	2.968	-6.032**	-2.010	-5.287**	-3.682*	-2.982**	1.025	-6.034**	-2.035	-3.278
	(1.762)	(1.230)	(4.757)	(2.901)	(1.360)	(2.425)	(1.948)	(1.484)	(4.302)	(2.868)	(2.442)	(3.523)
N	469	323	95	119	107	145	469	323	95	119	107	145

Bond maturities are measured in months. n represents the maturities for long term bonds. Short term bonds maturity is fixed at 1 month. Panel A. reports the estimated regression coefficients of the normalized spread $\frac{s_{n,t}}{n-m}$ $(m = 1)$ across different periods. Panel B. reports the estimated regression coefficients of the normalized spread, when CP factor is included as a proxy for expected excess returns. The Newey-West standard errors are reported in parentheses. The constant term is included in all, but not reported.

Table 2.4 Regression of Excess Return Prediction Using CP Factor

	n = 2	n = 3	n = 4	n = 6	n = 9	n = 12	n = 24	n = 36	n = 48	n = 60	n = 120
					Panel A. Coefficient Estimates of CP Factor						
m = 1	0.0413	0.0912	0.132	0.174	0.150	0.237	0.739*	1.296***	1.679***	1.817***	2.534**
	(0.0512)	(0.0872)	(0.120)	(0.172)	(0.210)	(0.255)	(0.395)	(0.482)	(0.579)	(0.663)	(1.083)
m = 2		0.0569	0.111	0.171	0.269	0.258	0.715**	1.189***	1.578***	1.807***	2.807***
		(0.0394)	(0.0721)	(0.127)	(0.175)	(0.208)	(0.342)	(0.438)	(0.537)	(0.627)	(1.047)
m = 3			0.0556	0.139	0.243*	0.405**	0.700**	1.143***	1.497***	1.725***	2.766***
			(0.0343)	(0.0854)	(0.130)	(0.174)	(0.285)	(0.380)	(0.476)	(0.564)	(0.966)
m = 4				0.0900*	0.190*	0.340**	0.641***	1.041***	1.365***	1.583***	2.570***
				(0.0540)	(0.100)	(0.141)	(0.244)	(0.334)	(0.423)	(0.509)	(0.892)
m = 6					0.119**	0.255***	0.572***	0.949***	1.267***	1.491***	2.447***
					(0.0517)	(0.0857)	(0.181)	(0.264)	(0.350)	(0.433)	(0.799)
m = 12							0.503***	0.870***	1.180***	1.447***	2.493***
							(0.103)	(0.185)	(0.261)	(0.342)	(0.704)
					Panel B. Regression R^2						
m = 1	-0.342	-0.191	-0.124	-0.0681	-0.0115	-0.0041C	0.0132	0.0246	0.0276	0.0242	0.0186
m = 2		-0.301	-0.165	-0.0843	-0.0165	0.00303	0.0248	0.0392	0.0455	0.0441	0.0403
m = 3			-0.274	-0.105	-0.0149	0.0251	0.0412	0.0590	0.0655	0.0635	0.0588
m = 4				-0.151	-0.0261	0.0313	0.0542	0.0731	0.0798	0.0770	0.0707
m = 6					-0.0382	0.0589	0.0896	0.112	0.119	0.114	0.0987
m = 12							0.263	0.260	0.258	0.245	0.208

Bond maturities are measured in months. n represents the maturities for long term bonds, m represents the maturities for short term bonds. Panel A. reports the estimated regression coefficient of the CP factor. The Newey-West standard errors are reported in parentheses. Panel B. reports the corresponding R^2 from the regressions. Similar to Cochrane and Piazzesi (2005) the constant term is excluded in all regressions. Hence R^2 can take negative value sometime. The underlying data are monthly zero-coupon bond yields over the period 1952:1 to 1991:2 from McCulloch and Kwon (1993).

Table 2.5: Maximum Likelihood Estimates (3-month)

Panel A. Maximum likelihood estimates				
	AR(1)		ARMA(1, 1)	
	Estimate	S.E.	Estimate	S.E.
δ_0	0.0336	(0.0190)	0.0236	(0.0208)
γ_0	0.4754	(0.1206)	0.5581	(0.1463)
δ_1	0.2032	(0.0749)	0.2076	(0.0614)
γ_1	0.8771	(0.0166)	0.8723	(0.0164)
σ_g	0.4340	(0.0749)	0.4391	(0.0692)
σ_y	0.3540	(0.0855)	0.3459	(0.0804)
σ_μ	0.5620	(0.0352)	0.5672	(0.0343)
$\rho_{g\mu}$	-0.0763	(0.1152)	-0.0621	(0.0690)
$\rho_{y\mu}$	-0.6554	(0.1431)	-0.6468	(0.1301)
ρ	-	-	-0.0211	(0.0195)
Panel B. Implied present- value model parameters				
A	0.5335		0.5710	
B	0.2150		0.2207	
C	0.5974		0.5886	
D	-		-0.0224	
Panel C. R^2 Values				
R^2_{er}	12%	-	12%	-
R^2_{cs}	79%	-	81%	-

Table 2.6: Variance Decomposition of the Yield Spread

Spec./ Data	Δ Expected Short Rate	Expected Excess Return	Covariance
AR(1)/ MK	1.85%	99.33%	-1.18%
AR(1)/ FB	0.66%	100.87%	-1.54%

Table 2.7: Maximum Likelihood Estimates (12-month)

Panel A. Maximum likelihood estimates				
	AR(1)		ARMA(1, 1)	
	Estimate	S.E.	Estimate	S.E.
δ_0	0.0198	(0.0140)	0.0194	(0.0123)
γ_0	0.2245	(0.1558)	0.2017	(0.0656)
δ_1	0.3531	(0.0647)	0.2300	(0.0858)
γ_1	0.9619	(0.0076)	0.9622	(0.0075)
σ_g	0.2130	(0.0182)	0.2275	(0.0162)
σ_y	0.4737	(0.0148)	0.4688	(0.0147)
σ_μ	0.3926	(0.0104)	0.3877	(0.0105)
$\rho_{g\mu}$	-0.2422	(0.0415)	-0.1372	(0.0575)
$\rho_{y\mu}$	-0.6638	(0.0234)	-0.7003	(0.0292)
ρ	-	-	0.0087	(0.0266)
Panel B. Implied present- value model parameters				
A	0.2192		0.2002	
B	0.3779		0.2212	
C	0.7384		0.7389	
D	-		0.0084	
Panel C. R^2 Values				
R^2_{er}	12%	-	12%	-
R^2_{cs}	29%	-	35%	-

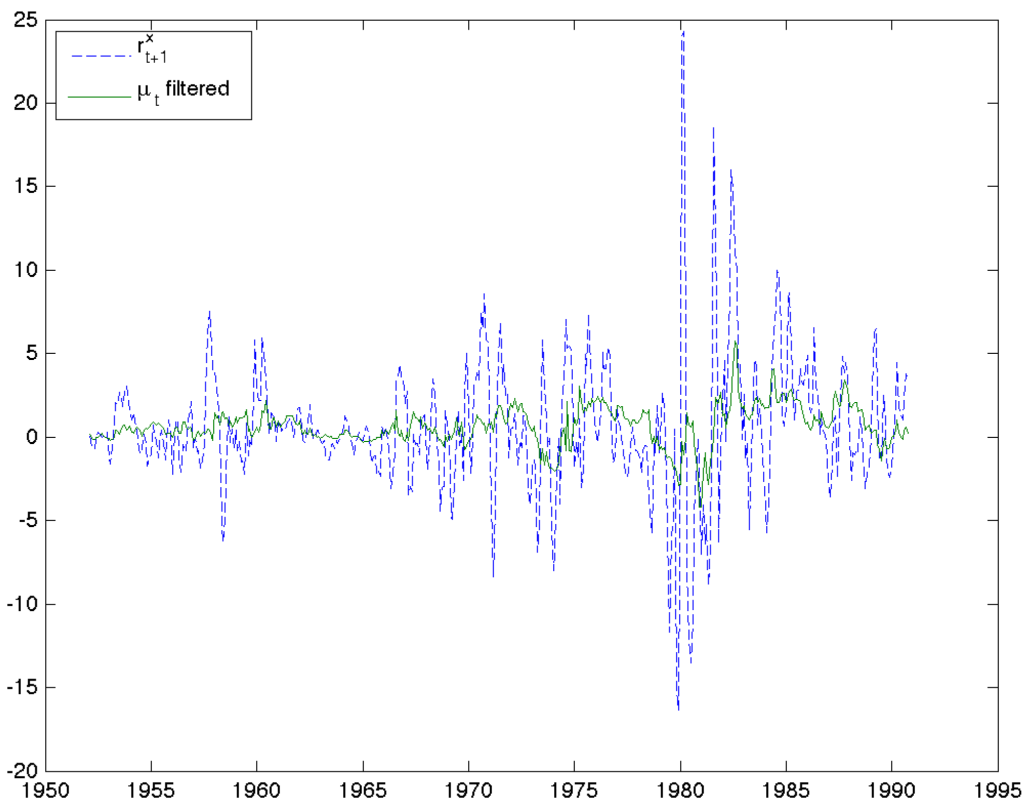


Figure 2.1: Filtered series for the expected excess return over MK 3-month short rate.

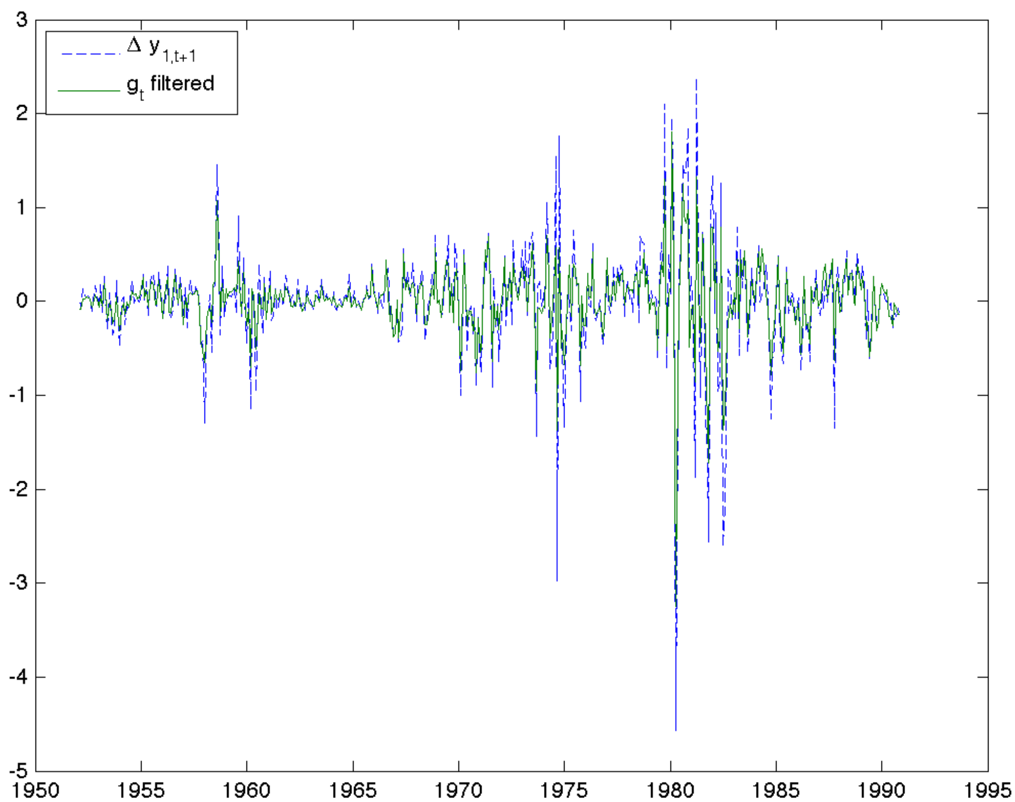


Figure 2.2: Filtered series for the expected short rate change of MK 3-month.

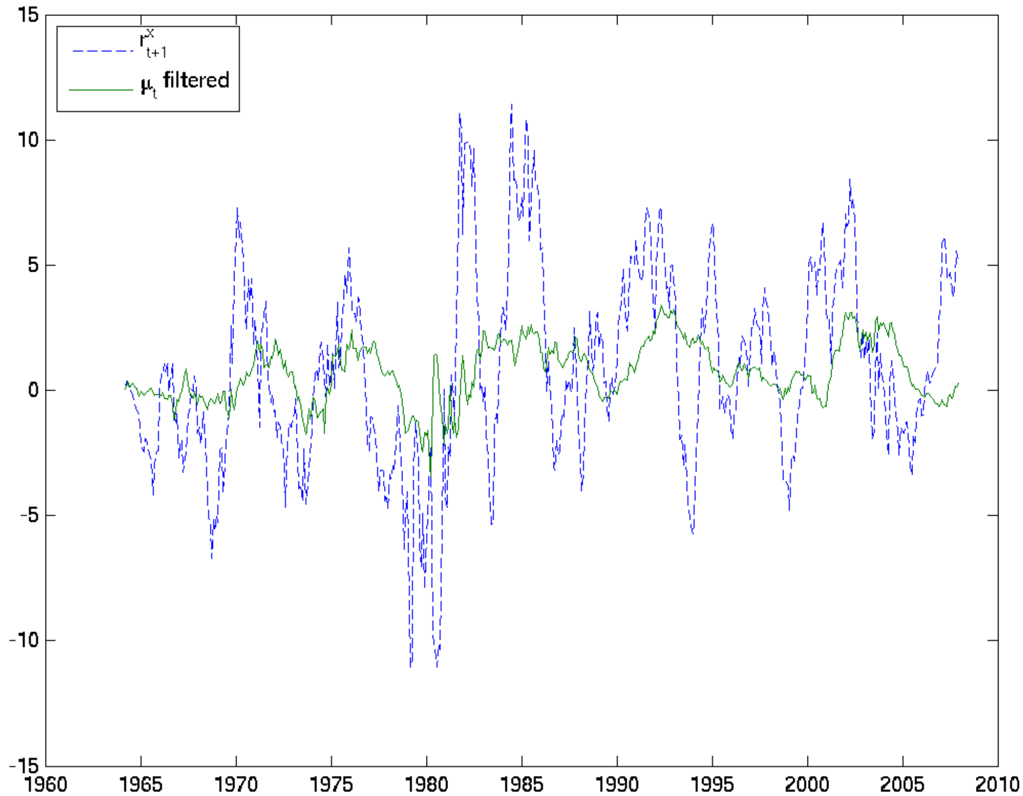


Figure 2.3: Filtered series for the expected excess return over FB 12-month short rate.

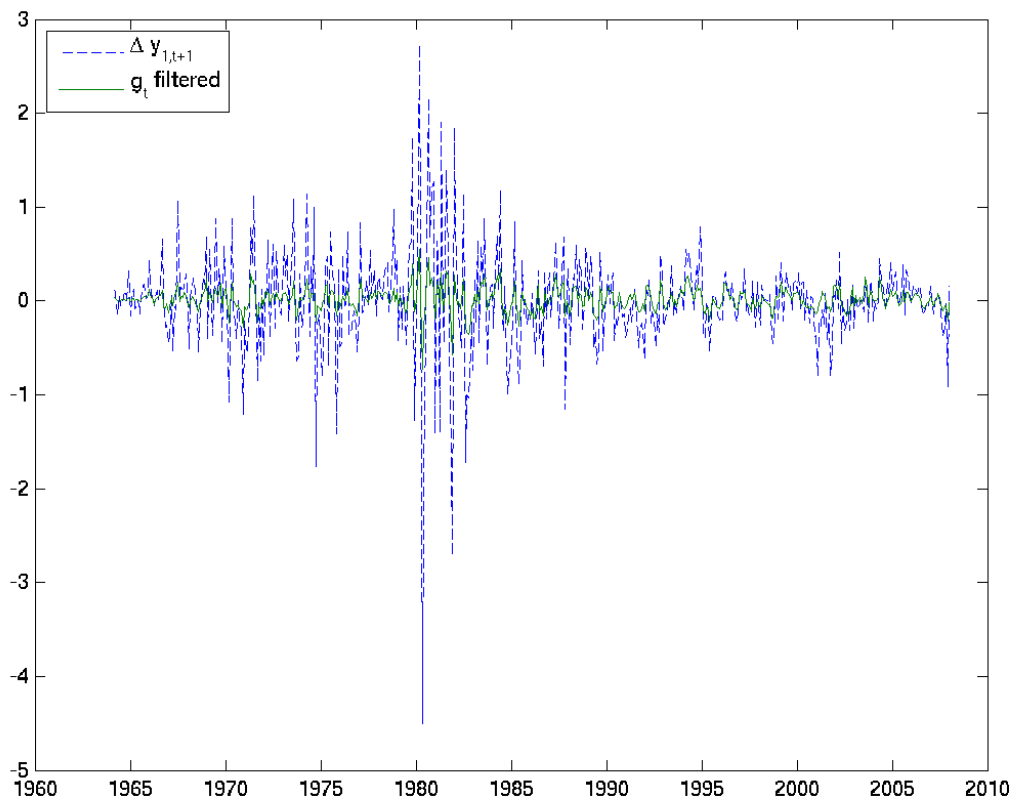


Figure 2.4: Filtered series for the expected short rate change of FB 12-month.

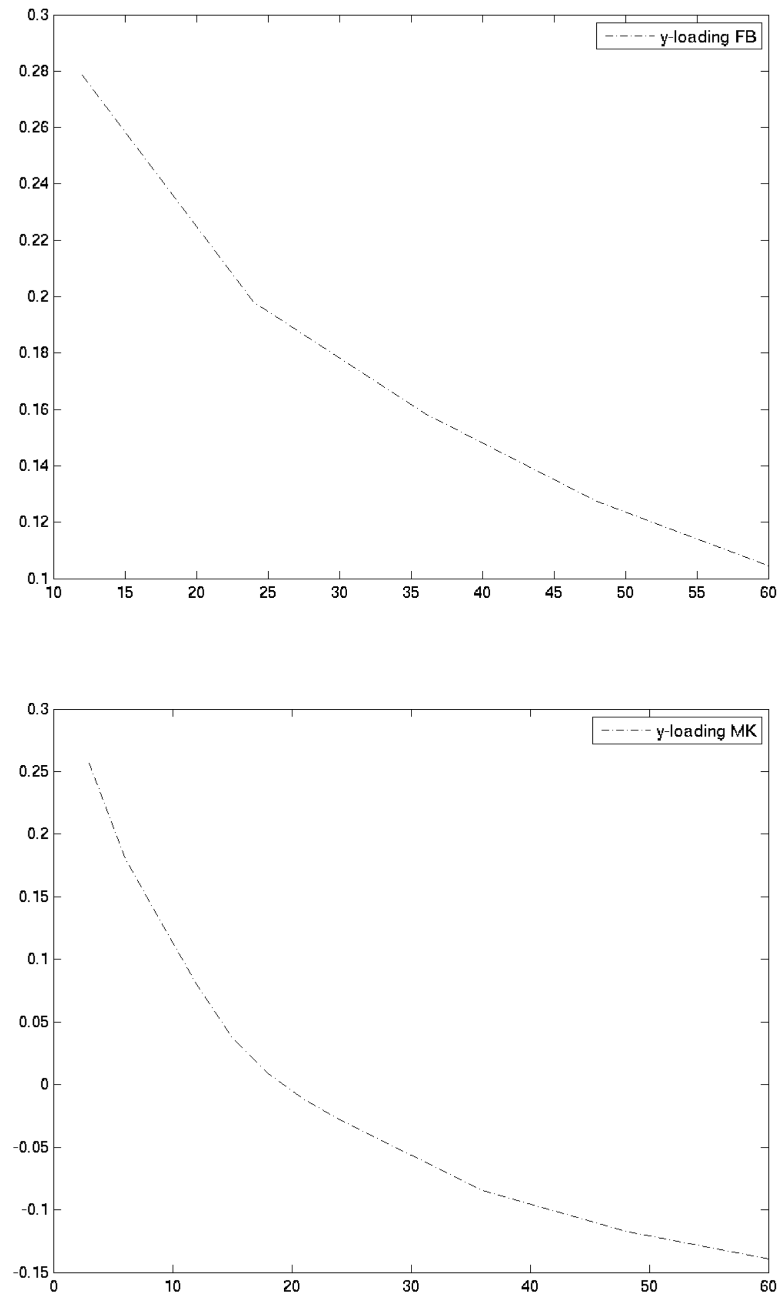


Figure 2.5: Loadings of identified shocks to unexpected short rate change across maturities.

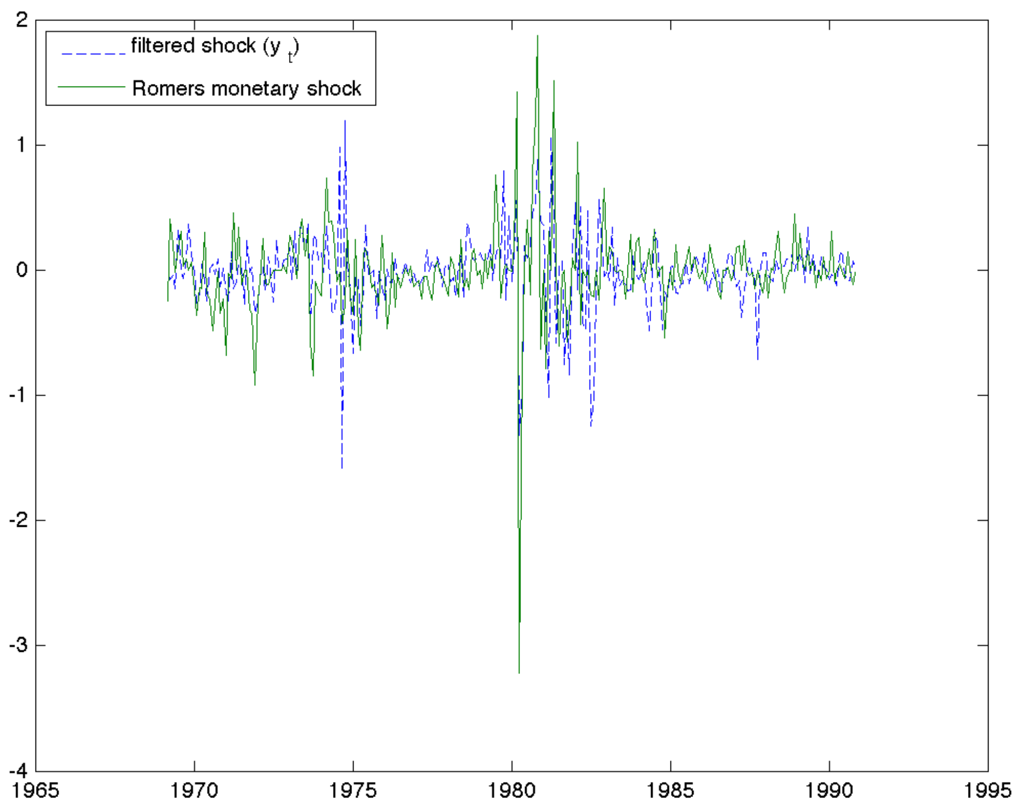


Figure 2.6: Shocks of expected short rate change and monetary policy shocks (MK data).

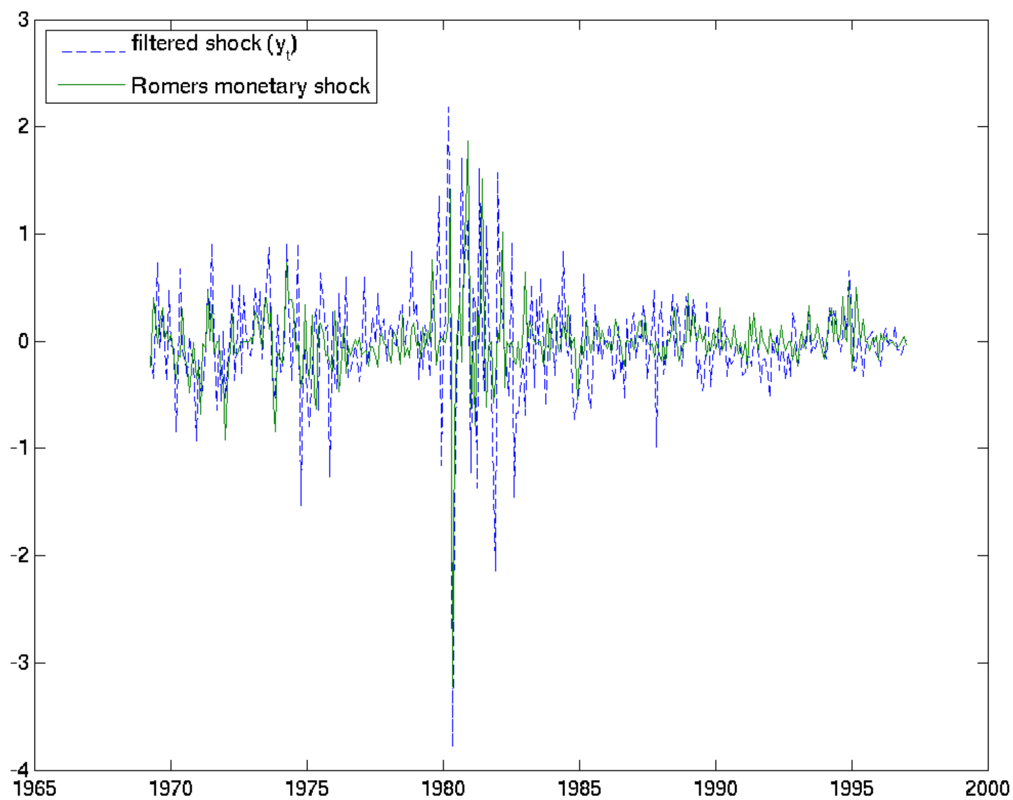


Figure 2.7: Shocks of expected short rate change and monetary policy shocks (FB data).

Chapter 3

Capital Structure and Firm Risk

3.1 Introduction

The core question in corporate finance is how firms finance their operations and whether the type of financing affects corporate outcomes. After the seminal work of Modigliani and Miller, many papers have been developed to explain the corporate capital choice. The leading theories in the current literature are trade-off theory, pecking order theory, and market timing theory. Empirical work has established several stylized facts on capital structure choice, yet it is still unsettled that how these facts are related to different theories. Traditionally, researchers treat firm observations at different times as equally important when studying firms' capital structure. However, empirical studies have shown that firms' capital structure is persistent and path dependent. This has two implications. First, it indicates that managers do not constantly make adjustments in firms' capital structure, because of either inattention or high adjustment cost. As a result, treating firm observations at different times as equally important could be problematic. Instead, one should be focusing on the periods that management teams are actively making capital structure choices, for instance, times when firms go public(IPO). Secondly, the stylized fact also implies that if we understand what affects a firm's capital structure choice at IPO, it helps us to a large degree understand its life-time capital structure.

In this chapter, I show that there is a strongly decreasing time trend in firms' leverage ratio at the time of their IPOs. Moreover, firms listed more recently remain more adverse to debt financing over the subsequent years post-IPO. Based on a simple static capital structure choice model, I explore several factors that might explain the documented trend such as aggregate market condition, corporate tax, and firm risk. By carefully examining the pattern in different periods and across different industries, I find that the risk associated with firm's operation is affecting firm's financing decision, and it has some potential to explain the time trend in firms' leverage ratio at IPO as documented in this chapter. However, it is puzzling that large proportion of the time trend is still unresolved.

The most related work is Baker and Wurgler (2002). They demonstrate that firms' leverage ratios are affected by the market valuation of their equities after IPO. They use the market to book ratio of the current back to the IPO date, weighted by issuance of equity and debt. They show that this market valuation effect on a firm's leverage position tends to be persistent and conclude that managers try to time the market when making financing decisions. Instead of looking at how a firms' capital structure evolves over time after IPO, I focus on the cross-section difference of firms' capital structure at IPO. Lemmon et al. (2008) also emphasize the persistency of firms' capital structure, but they do not pay attention to the change in firms' initial capital structure over time.

Furthermore, I consider several possible explanations for the downward time trend pattern of firms' leverage positions at IPO including the corporate tax rate, the aggregate market condition, the risk that associates with firms' operations, and the interest rate that firms faced. These factors are generally not controlled for in the empirical studies of the current literature. I include the aggregate market condition in order to capture the market-timing effect from Baker and Wurgler (2002). According to the trade-off theory, managers make capital structure choices balancing the tax benefit and the bankruptcy cost. Therefore the corporate rate should be important for capital structure decisions. The relationship between firm risk and its leverage position can also be established using the trade-off theory. The idea is that when firm risk is high, the volatility of the firm's cash flow will be high as well. Thus given the outstanding debt level, at any point of time the expected bankruptcy cost is high. Because the probability of meeting the debt obligation is low when the volatility of the firm's cash flow is high. Under the static trade-off model, Bradley et al. (1984) have shown that for reasonable parameter values, the relation between leverage ratio and firm risk is negative. The same holds in the static analytical model of Leland (1994), and in the dynamic model of Goldstein et al. (2001). All the models above use a continuous time model, and use numerical method to derive the relationship. To fix the idea, I develop a simple two periods model, in which I show analytically how the firm risk affects the firm's optimal debt level, and hence the optimal leverage ratio. Leland (1994) model also implies that lower interest rate, *ceteris paribus*, will lead to lower leverage ratio, although the interest rate is assumed to be constant in that model. For that, I look at the US prime rate over the period of 1970 to 2006 as a proxy of the interest rate to discuss its role.

The rest of the chapter is organized as follows. Section 3.2 presents a two period model to capture the link between firm risk and leverage ratio. Section 3.3 describes the data used for my empirical analysis. Section 3.4 demonstrates the empirical evidence for the motivation for the study of firms' capital structure at IPO. Section 3.5 documents the downward time trend in firms' leverage position at IPO. Section 3.6 talks about the implication of firm risk and provides some empirical evidence. Section 3.7 concludes.

3.2 A Simple Model

I develop a simple two period model to illustrate how the firm risk affects the firm's leverage position. A firm has value V_0 at time 0 , which is based on a project that yields a stochastic return in period 1. Hence the value of firm at period 1 V_1 is stochastic. Assume $V_1 = \max\{0, \tilde{V_1}\}$, where $\tilde{V_1}$ is normally distributed[1], $\mathcal{N}(\mu, \sigma^2)$. At period 0, firm decides how much they issue debt, which is the amount of the coupon payment at period 1. The debt issuance is financed by equity. If the firm is able to make the promised payment at period 1, it does so and enjoys a tax benefit with rate τ. If firm is not able to deliver the promised payment, then debt holders will take over the firm. In this case, the firm declares bankruptcy and suffers a bankruptcy cost of rate α. The interest rate is normalized to zero[2] and firm manager is maximizing firm value at period 0 by choosing the optimal debt level.

Firm issues debt by promising an amount of payment C at period 1. If firm is not able to deliver the payment at period $1(V_1 < C)$, debt holder takes over the firm. Thus if no bankruptcy is filed, the gain from debt issuance is τC. Otherwise, firm suffers a bankruptcy cost αV_1. Therefore, the firm value at period 0 is affected by the debt issuance. The expected gain is $\mathbb{P}\left\{V_1 > C\right\}\tau C$, and the expected loss is $\mathbb{P}\left\{V_1 < C\right\}\mathbb{E}\left[V_1|V_1 < C\right]\alpha$. The manager's problem becomes:

$$\max_{C} \qquad V_0 + \mathbb{P}\left\{V_1 > C\right\}\tau C - \mathbb{P}\left\{V_1 < C\right\}\mathbb{E}\left[V_1|V_1 < C\right]\alpha \tag{3.1}$$

Let $F(.)$ denotes CDF for V_1, and $f(.)$ be the PDF, the above expression is equivalent to

$$\max_{C} \qquad V_0 + (1 - F(C))\,\tau C - \alpha \int_{-\infty}^{C} v_1 f(v_1) dv_1 \tag{3.2}$$

F.O.C:

$$(1 - F(C))\,\tau - \tau f(C)C - \alpha C f(C) = 0 \tag{3.3}$$

S.O.C:

$$-f(C)\tau - (\tau + \alpha) f(C) - (\tau + \alpha) C f'(C) \tag{3.4}$$

Recall that $V_1 = \max\{0, \tilde{V_1}\}$, and $\tilde{V_1} \sim \mathcal{N}(\mu, \sigma^2)$, let $\Phi(.)$ denote the CDF for $\mathcal{N}(0,1)$, and $\phi(.)$ be the PDF. Let C^* be the optimal debt level. Then it solves equation (3.3). As long

[1] In this simple model, I assume that investors are risk neutral and the expectations are taken under physical measure.

[2] The assumption of the interest rate ignores the time dynamics of interest rate. As I will discuss later, the US Prime Rate, as a proxy of the interest rate, varies over time. It suggests that a model with stochastic interest rate process might be more appropriate. For the moment, I am focusing on other factors such as corporate tax and firm risk. A more comprehensive examination of the interest rate effect is left for future research.

as $C^* > 0$[3], I can express equation (3.3) in the following way:

$$\left(1-\Phi\left(\frac{C^*-\mu}{\sigma}\right)\right)\tau = (\tau+\alpha)\phi\left(\frac{C^*-\mu}{\sigma}\right)\frac{C^*}{\sigma} \tag{3.5}$$

What I am interested in is $\frac{\partial C}{\partial \sigma}$, so I take derivative of both sides of equation (3.5). Recall that $\phi(x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}}$ and $\phi'(x) = -x\phi(x)$, the right hand side of equation (3.5) after taking derivative becomes

$$\begin{aligned}
RHS &= (\tau+\alpha)\left\{\frac{C^*}{\sigma}\frac{\partial}{\partial\sigma}\left[\phi\left(\frac{C^*-\mu}{\sigma}\right)\right] + \phi\left(\frac{C^*-\mu}{\sigma}\right)\frac{\partial}{\partial\sigma}\left[\frac{C^*}{\sigma}\right]\right\} \\
&= (\tau+\alpha)\frac{C^*}{\sigma}\left[-\phi\left(\frac{C^*-\mu}{\sigma}\right)\frac{C^*-\mu}{\sigma}\frac{\partial}{\partial\sigma}\left[\frac{C^*-\mu}{\sigma}\right]\right] \\
&\quad + (\tau+\alpha)\phi\left(\frac{C^*-\mu}{\sigma}\right)\left(\frac{1}{\sigma}\frac{\partial C^*}{\partial\sigma} - \frac{C^*}{\sigma^2}\right) \\
&= -(\tau+\alpha)\phi\left(\frac{C^*-\mu}{\sigma}\right)\left(\frac{\partial C^*}{\partial\sigma}\frac{1}{\sigma} - \frac{C^*-\mu}{\sigma^2}\right)\frac{(C^*-\mu)C^*}{\sigma^2} \\
&\quad + (\tau+\alpha)\phi\left(\frac{C^*-\mu}{\sigma}\right)\left(\frac{\partial C^*}{\partial\sigma}\frac{1}{\sigma} - \frac{C^*}{\sigma^2}\right)
\end{aligned}$$

Therefore, when I take derivative on both sides of equations (3.5), here is what I have,

$$\begin{aligned}
&-\tau\phi\left(\frac{C^*-\mu}{\sigma}\right)\left(\frac{\partial C}{\partial\sigma}\frac{1}{\sigma} - \frac{C^*-\mu}{\sigma^2}\right) = \\
&(\tau+\alpha)\phi\left(\frac{C^*-\mu}{\sigma}\right)\left(\frac{\partial C^*}{\partial\sigma}\frac{1}{\sigma} - \frac{C^*}{\sigma^2}\right) \\
&\quad - (\tau+\alpha)\phi\left(\frac{C^*-\mu}{\sigma}\right)\left(\frac{\partial C^*}{\partial\sigma}\frac{1}{\sigma} - \frac{C^*-\mu}{\sigma^2}\right)\frac{(C^*-\mu)C^*}{\sigma^2}
\end{aligned} \tag{3.6}$$

Rearranging terms I have,

$$\begin{aligned}
&\left\{-\frac{\tau}{\sigma} - \frac{\tau+\sigma}{\sigma} + (\tau+\sigma)\frac{C^*(C^*-\mu)}{\sigma^3}\right\}\frac{\partial C^*}{\partial\sigma} = \\
&\quad -\tau\frac{C^*-\mu}{\sigma^2} - \frac{(\tau+\alpha)C^*}{\sigma^2} + (\tau+\alpha)\left(\frac{C^*(C^*-\mu)^2}{\sigma^4}\right)
\end{aligned} \tag{3.7}$$

From equation 3.7, it is easy to verify that as long as $C^* \in (0,\mu)$, $\frac{\partial C^*}{\partial\sigma} < 0$. Now rearranging

[3] I will verify this condition later.

equation (3.3), I have

$$(1 - F(C^*))\frac{\tau}{\tau + \alpha} = C^* f(C^*) \tag{3.8}$$

Hence, for any distribution function $F(.)$ and $\tau > 0$, $C^* \geq 0$. If $F(C^*) < 1$, then $C^* > 0$, which is the case for normal distribution. To show that $C^* < \mu$, I will discuss the case of normal distribution only, in addition to a technical condition that $\mu > \sigma\frac{\sqrt{2\pi}}{2}$. In such case, $F(C) = \Phi\left(\frac{C-\mu}{\mu}\right)$, and $f(C) = \frac{1}{\sigma}\phi\left(\frac{C-\mu}{\sigma}\right)$. The LHS of equation (3.8) is decreasing function of C, and it is less than $\frac{1}{2}$ when $C = \mu$. On the other hand, RHS has derivative $\frac{1}{\sigma}\phi\left(\frac{C-\mu}{\sigma}\right) - \frac{C(C-\mu)}{\sigma^2}\phi\left(\frac{C-\mu}{\sigma}\right)$. It is positive if $C \in (0, \mu)$, indicating that it is an increasing function over the range $(0, \mu)$. Notice that the RHS has value 0 when $C = 0$, while LHS is positive. Moreover, the RHS has value $\frac{\mu}{\sigma\sqrt{2\pi}}$, which is greater than the value of LHS from the technical condition. By continuity, $\exists C \in (0, \mu)$, satisfies equation (3.8). From previous analysis, SOC is negative for such value, implying it is a local maximum, and $\frac{\partial C^*}{\partial\sigma} < 0$. Hence the value of debt that firm is willing to issue decreases because (1) coupon payment decreases, (2) probability of bankruptcy increases. The main message from this simple model is that a firm's optimal leverage position goes down as it becomes riskier. Therefore if the firm risk has been rising over the past 30 years at the stage of IPO, it may offer some explanatory power for the downward time trend in firms' leverage ratio at the time of IPO. In the next section, I will describe the data set used for empirical analysis.

3.3 Data and Summary Statistics

The main sample consists of firm level annual data from Standard & Poor's COMPUSTAT. I obtain firms' IPO dates and founding dates from Loughran and Ritter (2004), and Security Data Company (SDC) data. Jay Ritter's data contains 8462 firms went public between 1975 and 2006. Among these, 217 firms' founding dates are missing[4]. Similar to Baker and Wurgler (2002), I use the IPO date from SDC data whenever the information is not available in Jay Ritter's data set. To form the main sample, I start with all COMPUSTAT firms appearing at any point between 1962 and 2006, then select the firms for which I can determine their IPO dates and their founding dates using Jay Ritter's data. I further restrict the sample to exclude financial firms with an SIC code between 6000 and 6999, utility firms with SIC code between 4900 and 4999[5], and firms with a minimum book value of assets below $10 million. The merged data has 6549 firms, and the IPO density is shown in figure 3.1.

I define book debt as total assets [Compustat annual item 6] minus book equity. I define

[4]In the data, these dates are recorded either 1900 or 1901, meaning the founding dates are no later than 1900.

[5]The capital structure of firms in utility or financial industry is heavily influenced by regulation, therefore they are excluded from the analysis.

book equity as total assets less total liabilities [Item 181] and preferred stock [Item 10] plus deferred taxes [Item 35] and convertible debt [Item 79]. When preferred stock is missing, it is replaced with the redemption value of preferred stock [Item 56]. Book leverage is then defined as book debt to total assets. I drop firm-year observations where the resulting book leverage is above one[6], I define market leverage as book debt divided by total assets minus book equity plus market equity. For the rest of the chapter, the term leverage ratio is referred to as the market leverage ratio[7]. Market equity is defined as common shares outstanding [Item 25] times price [Item 199]. These definitions follow Fama and French (2000). Market to Book ratio is defined as assets minus book equity plus market equity all divided by assets. Asset tangibility is defined as net plant, property and equipment [Item 8] divided by total assets and expressed in percentage terms. Profitability is defined as earnings before interest, taxes and depreciation [Item 13] divided by total assets and expressed in percentage terms. Size may increase leverage if large firms are less likely to enter financial distress. It is measured as the log of net sales [Item 12][8]. The summary statistics of key variables are presented in table 3.1. The first two columns reports the mean and standard deviation using the whole sample, and the last two columns use subsample of firm observations at the time of IPO only. I see from table 3.1 that firms have lower leverage position when going public comparing to their leverage position afterwards. At the time of IPO, firms' leverage ratio on average is about 20%, while the average leverage ratio is about 30% using the whole sample. Moreover, the market-to-book ratio is also higher at the time of IPO. One can argue that firms tend to IPO when market overvalue their assets. This can be observed more directly from Figure 3.1. During 1990s (the internet bubble), there are more IPOs relative to other periods.

In the next section, I will discuss the empirical evidence of persistence of firms' initial capital structure, which shows why firms' capital structure at IPO is important.

3.4 Motivation

As I mentioned in the introduction, one important reason for study of firms' capital structure at IPO is the persistence of firms' capital structure. Therefore I analyze to what extent a firm's initial leverage position (in the year of IPO) explains firm's future leverage ratio. I adopt an approach similar to Lemmon et al. (2008), and use the following specification:

$$MLR_{it} = \beta_1 iniMLR_i + \beta_2 Size_{it} + \beta_3 MTB_{it} + \beta_4 Prof_{it} + \beta_5 Tang_{it} + Ind_i + \epsilon_{it}$$

where MLR_{it} is the market leverage ratio of firm i at time t; $iniMLR_i$ is the initial leverage ratio of firm i; $Size_{it}, MTB_{it}, Prof_{it},$ and $Tang_{it}$ are the size, market to book ratio, prof-

[6]Following the procedure in Baker and Wurgler (2002)

[7]The empirical results are robust using book leverage ratio.

[8]Baker and Wurgler (2002) used the same measure. It may be more appropriate to adjust for inflation.

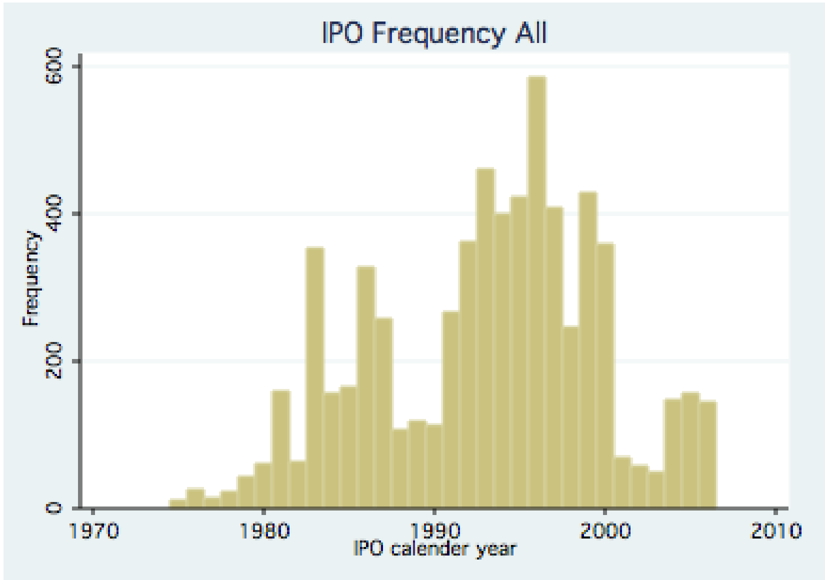


Figure 3.1: IPO density

itability, and tangibility of firm i at time t respectively. Ind_i are FF 10 industry dummies to control for the industry fixed effect. The persistency of firm's leverage ratio can be captured by the estimate of β_1. The above specification is tested using three subsamples. The results are presented in table 3.2. The estimates in the first column are based on firm-year observations that are 5 years after their IPO years. And the second and the third column correspond to samples of observations that are 10 years and 20 years after IPO respectively. The estimate of β_1 is significant in all three samples. Note that the estimate of β_1 is about 0.54 for firm observations that are 5 years after IPO, 0.46 for 10 years after IPO, and still about 0.31 for even 20 years after IPO. Lemmon et al. (2008) defines initial leverage ratio as the first non-missing value of leverage. They obtain an estimate of 0.24 using 1965-2003 sample (all firms). When they restrict to firms that survive for at least 20 years, the estimate is about 0.36[9]. While I obtain a similar estimate when using firm observations 20 years post IPO, estimates of 5-year-post-IPO sample and 10-year-post-IPO are much larger in magnitude comparing to that of 20-year-post-IPO sample. This shows strong persistence of firms' initial capital structure. Therefore, firm's leverage ratio at the time of its IPO predicts firm's capital structure afterwards. Now having shown its persistence, let's move on analyzing firms' capital structure at IPO.

[9]The marginal effect obtained in Lemmon et al. (2008) is 0.06 and 0.09 per one-standard deviation change in the initial leverage for the whole sample and surviver sample respectively. And the standard deviation of market leverage ratio is 0.25 in their sample. Thus I multiply their estimates by 4 when comparing with my estimates.

3.5 Time Trend

Until now I have shown how important a firm's initial capital structure is. The next step is to analyze firms' leverage ratio at time of IPO. Figure 3.2 shows a simple plot of average leverage ratio at IPO across different IPO years. The best fit line in the figure has a negative slope. The result is similar using book leverage ratio.

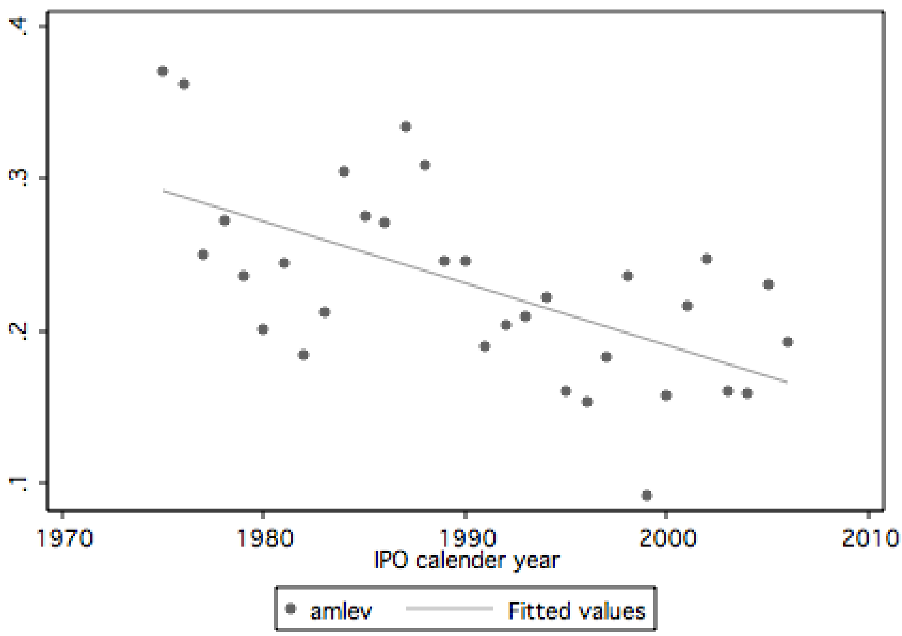


Figure 3.2: Market Leverage Ratio

To check the robustness of the trend, I regress marker leverage ratio at IPO on the time of firm's IPO ($Iyear$), controlling for the industry fixed effects (Fama-French 10 industry dummies, Ind_i), and firm size (Size), profitability (Prof), market to book ratio (MTB), asset tangibility (Tang), and firm age (Age), which is defined as the difference between firm's IPO date and founding date:

$$MLR_i = \beta_1 Iyear_i + \beta_2 Size_i + \beta_3 MTB_i + \beta_4 Prof_i + \beta_5 Tang_i + \beta_6 Age_i + Ind_i + \epsilon_i. \quad (3.9)$$

The reason I include age variable is that Fink et al. (2005) and Jovanovic and Rousseau (2001) find firms are becoming younger at the stage of IPO. The maturity of a firm will possibly affect its leverage positions. For instance, a less mature firm tends to have more volatile cash flow or higher probability of bankruptcy. As predicted by the model, this could lead to a lower leverage position. It is also possible that young firms are constraint from debt financing because it is more difficult for young firms to obtain loans from banks. In my model, this effect can not be captured because I do not model the supply side corporate debt. In either case, firm age should be included when studying firms' leverage ratio at IPO.

The result from the whole sample including 5550 firms are presented in the column (1) in table 3.3. After controlling for these standard factors and industry fixed effect, I see that the coefficient for *Iyear* is negative and it is both statistically and economically significant. According to the estimation, the market leverage ratio of two firms that go to IPO 20 years apart, ceteris paribus, could differ as much as $20 \times 0.6\% = 12\%$. This is quite large considering the leverage ratio in aggregate level is about 30%(20% at the time of IPO). The signs of estimates for the other factors are consistent with the finding in current literature. For example, there is negative correlation between firm profit and leverage ratio; bigger firms and firms with more tangible assets tend to have higher leverage ratio. Though firm age is generally not included in the current literature, it has positive effect on leverage. An older firm is likely to have more stable operating cash flow or better reputation, which makes it easier to obtain loans from banks. Moreover, to show the result is not driven by some anomaly or some rare event in certain period, I split the sample into two periods, pre-1990 and post-1990[10]. The results are listed in column (2) and (3) respectively. The results are quite similar to the estimation using the whole sample. The coefficient on IPO year(Iyear) for post-1990 is a little less than pre-1990 subsample, yet it is still both statistically and economically significant. Alternatively, I use the post-1980 subsample to test how much the high leverage of firms listed in 70s (see Figure 3.2) affect the results. The estimates barely change compared to the estimates using the whole sample. In addition, when I divide the sample into three subsamples: 1970-1985, 1985-1995, and 1995-2006 (untabulated), the coefficient on IPO year remain negative and significant at 5% level, ranging from -0.002 to -0.008.

I also check the robustness across industries, estimating the the model in equation (3.9) separately in each of the 9 industries (and dropping the industry dummies). Results are presented in Table 3.4. The coefficients of Iyear(IPO year) are all negative, and seven of them are statistically significant. For the industries that with insignificant estimates, I have less observations relative to other industries (except for healthcare), which makes it more difficult to identify the time trend in these industries. Nevertheless, it is also possible that the factors that generate the downward time trend of firms' capital structure do not change as much in these two industries.

So far I have demonstrated that the leverage ratio at the time of IPO is lower for firms which went public more recently, controlling for industry fixed effect and other factors that influence firms; capital structure. I now ask: to what extent does this time trend influence firms' financial decision in the future? Put together the facts that firms listed more recently

[10]The reason I choose 1990 as the pivoting year is that my sample consists of observations from 1975 to 2004, about 30 years span. Year 1990 is right in the middle. Moreover, I want to see if the trend is driving by the internet bubble in 90s.

have lower leverage ratio initially and the persistence feature in firms' capital structure discussed earlier, it is very likely that firms listed more recently are more conservative in debt financing. This might imply firms that went public more recently deviate more from the pecking order behavior. Thus I adopt the following two specifications:

$$\Delta D_{it} = \beta_1 DEF_{it} + \beta_2 Iyear_i + X'_{it}\gamma + \epsilon_{it} \tag{3.10}$$

$$\Delta D_{it} = \beta_1 DEF_{it} + \beta_2 Iyear_i + \beta_3 DEF_{it} \times Iyear_i + X'_{it}\gamma + \epsilon_{it} \tag{3.11}$$

where ΔD_{it} is the change of long term debt for firm i at time t[11], DEF_{it} is the external financing deficit for firm i at time t. The two variables ΔD and DEF are constructed according to work by Frank and Goyal (2003):

$$DEF_{it} = DIV_{it} + I_{it} + \Delta W_{it} - C_{it}$$

DIV is cash dividends; I net investment (capital expenditures + increase in investments + acquisitions + other uses of funds - sale of PPE - sale of investment);[12] ΔW the change in working capital (change in operating working capital + change in cash and cash equivalents + change in current debt);[13] and C cash flow after interest and taxes (income before extraordinary items + depreciation and amortization + extraordinary items and discontinued operations + deferred taxes + equity in net loss (earnings) + other funds from operations + gain (loss) from sales of PPE and other investments).[14] Variables that might affect the firm's attitude toward debt issuance such as size, profitability, tangibility, market to book ratio, corporate tax rate and industry dummies, are included in X_{it}.

The difference between the two specifications (3.10) and (3.11) is the interaction term between financing deficit DEF and IPO year $Iyear$. I could tell whether more recently listed firms have a lower growth rate of debt on average by looking at the estimate of β_2 from specification (3.10). Specification (3.11) aims to capture if firms that go public more recently use debt more conservatively when financing their operation by checking the estimate of coefficient before the interaction term, β_3.

The results are listed in Table 3.5. Let's first look at column (1). The coefficient on financing deficit is much less than one. This can be seen as the evidence against pecking

[11] I measure net debt issuance as the difference between long-term debt issuance (item 111) and long-term debt reduction (item 114), normalized by total asset (item 6).

[12] For firms reporting format codes 1 to 3, net investment is items 128 + 113 + 129 + 219 - 107 - 109; for firms reporting format code 7, it is items 128 + 113 + 129 - 107 - 109 - 309 - 310. When items are missing or combined with other items, I code them as 0.

[13] For format code 1, this is items 236 + 274 + 301; for codes 2 and 3, -236 + 274 âĹŠ 301; for code 7, -302 - 303 - 304 - 305 - 307 + 274 - 312 - 301. All items, excluding item 274, are replaced with 0 when missing or combined with other items.

[14] For codes 1 to 3, this is items 123 + 124 + 125 + 126 + 106 + 213 + 217 + 218. For code 7, this is items 123 + 124 + 125 + 126 + 106 + 213 + 217 + 314. Items are coded as 0 when missing or combined with other items.

order theory, which is similar to the result obtained by Shyam-Sunder and Myers(1999). The coefficient for IPO year is negative and statistically significant. Controlling for other factors, firms that go public twenty years later issue about 4% (of book value of firm total assets) less debt annually on average. This is economically significant, especially when taking into consideration that in sample the mean of annual debt issuance is about 1.1% of book value of the firm's total assets. In column (2) of Table 3.4, the coefficient of the interaction term, β_3, is negative and statistically significant. Based on the estimation, the proportion of financing deficit that is covered by debt issuance is about 36% lower for a firm that goes public twenty years later. This confirms my hypothesis earlier that firms listed more recently deviate more from pecking order behavior. Therefore, whatever factors that drive downward time trend in the leverage ratio at IPO also affect firm's attitude towards debt issuance subsequently: firm which went public more recently is more adverse to debt issuance when controlling for financing deficit.

3.6 Discussion

In previous section, I have shown that the leverage ratio of firms at their IPO year is lower for those which go public more recently. In addition, the firms listed more recently are more adverse to debt issuance when financing. Here I focus on the time trend in the leverage ratio of firms at the time of IPO and discuss some factors that might explain the observed pattern.

One important factor affecting the capital structure choice is the corporate tax rate. One benefit for firms to issue debt is that the interest payment on debt is a tax-deductible expense. Thus if the corporate tax rate is high, then firms have strong incentives to raise debt, which creates a positive correlation between the tax rate and firm's leverage position. The corporate tax rate is, however, overlooked in the empirical studies of capital structure literature. To control for its effect, I use the top marginal tax rate on corporations. There are several drawbacks of such measure. First, this is the rate applicable at the federal level on domestic firms. In addition, the effective corporate tax rate may be higher due to the imposition of corporate level taxes on dividend or other distributions. Figure 3.3 shows the tax rate over the period from 1975 to 2007.

Another possible explanation for the observed pattern is firm risk as derived from the simple model in the earlier section. High firm risk means that the volatility of firm's cash flow is high. At a given level of corporate debt, the probability of meeting the debt obligation is low if the firm risk is high. Therefore, high firm risk discourage managers from raising corporate debt because the cost of debt issuance for the firm is high. The implied correlation between firm risk and leverage ratio is negative. I measure firm risk using the volatility of firms' cash flow. I use COMPUSTAT quarterly data to construct this variable of cash flow volatility, $VOLCF$. Cash flow is defined as the sum of earnings before extraordinary

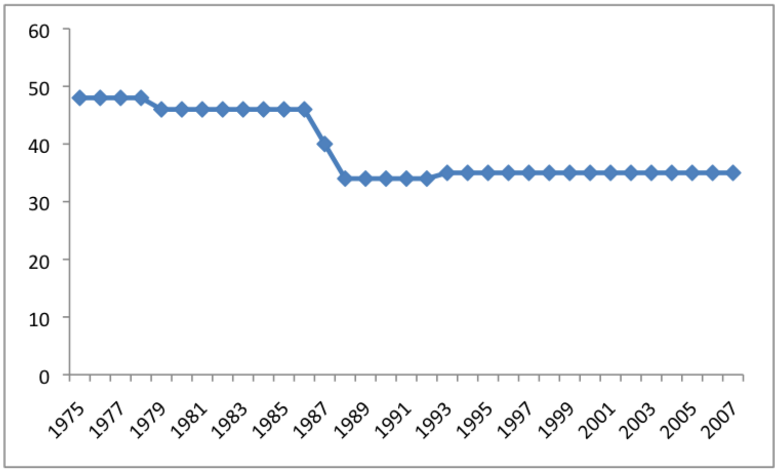


Figure 3.3: Historical Corporate Top Tax Rate

items(item 41) and depreciation (item 77) over total firm book value at the beginning of the period (item 44). The measure of volatility is the standard deviation of cash flow within 4 years after IPO. I drop the firms that has less than 2 years observations. This measure has many drawbacks. It suffers from seasonality issue. It has been documented that cash flow data has persistent component. What I really want to obtain is the shocks to a firm's cash flow, and compute volatility from that. Therefore I have to impose a structural specification of cash flow. For the moment, I will ignore these issues, and treat it as a rough estimate of firm risk. To prevent the result from being affected by outliers, I winsorize the volatility measure at upper and lower 1 percentile. When merged with the original data set, there are now 4370 firms in sample.

Finally, I include the market price earning ratio from Shiller's website to control for the aggregate market condition. Aggregate market condition may affect the timing of IPO hence the capital structure of the firm (Baker and Wurgler (2002)).

Adding these factors to the baseline equation (3.9), I have the following specification:

$$MLR_i = \beta Iyear + X_i'\gamma + Z_i'\theta + \epsilon_i.$$

where X_i is firm characteristic controls at the time of IPO (baseline controls), including size tangibility profitability, market-to-book ratio, firm age, and industry dummies. Z_i represents newly added factors. I look at changes in the estimates of β when choosing different factors included in Z_i.

Table 3.6 shows estimates of β using different sample periods. The first column lists the additional controls variables. Estimates which are significant at 5% are in bold. In most cases, adding additional controls does not help resolve the downward time pattern in firms' leverage ratio at IPO. For the pre-90 sample, however, firm risk measure appears an important factor explaining the time pattern as the estimate of β turns insignificant. Table 3.7 lists estimates of β across 10 Fama-French industries. Additional control variables help explain the time pattern for some industries such as manufacturing, energy and high-tech industry. For the telecommunication industry, the estimate become positive and significant when controlling for all additional variables. Nevertheless, the pattern is still present in other industries, such as durables, shops, etc. To see which variable is the most important factor for the time pattern, I can look at changes in the estimate when including control variables individually. The market price earning ratio does not appear as important as the other two factors. The estimate of β does not respond much when the market PE ratio is included. Firm risk measure appears to be essential as the magnitude of the time trend (β) reduces significantly for several industries (e.g. non-durables, energy, shops). If firm risk is one of the factors that generating the time pattern, then the evidence suggest that firms are becoming riskier at their IPO stages. This is confirmed by other empirical work. Campbell et al. (2001) find that over the period from 1962 to 1997, there has be a noticeable increase in firms' idiosyncratic risk component in their equity returns.

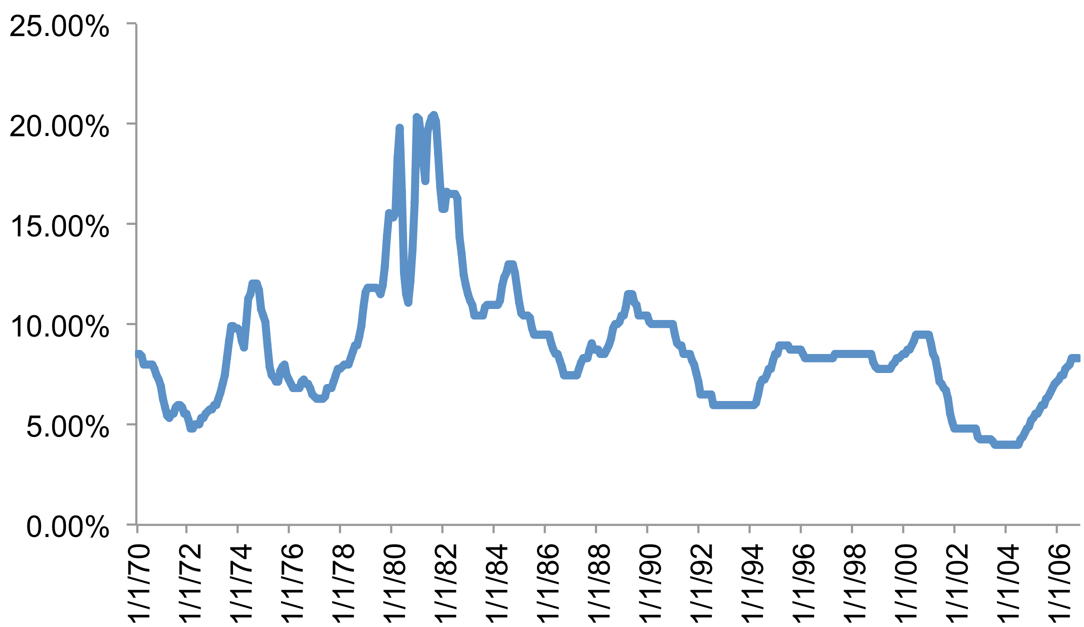


Figure 3.4: Historical US Prime Rate

Another factor that may affect firms' leverage ratio is interest rate firms are facing. According to Leland (1994), the interest rate could play a role in the downward time trend in firms' leverage ratios at the time of their IPOs. Figure 3.4 shows historical monthly US Prime Rate (the rate at which banks lend money to its biggest and best customers) over the the period from 1970 to 2006. It shows that the Prime Rate was falling dramatically during

1980 to 1988, therefore it may be related to the trend documented in this chapter,although it is not clear how important the factor is. For instance, over 1976-1980, the rate increased a lot, yet we do not see a similar jump in the leverage ratio at all. If we look at the figure of firms market leverage ratio prior to 1980, the downward trend is quite strong, although we do not have many observations in that period. Moreover, from the estimation using the post-90 subsample, we have a strong downward trend, yet it does not seem to be a deterministic trend in the Prime Rate post 1990. It is still interesting to see how much of the downward trend in firms' leverage positions can be explained by the interest rate. I am thinking about using a model with stochastic interest rate to capture the time dynamics of the interest rate to address that question better.

Overall, I find that additional control variables offers on limited explanations for the observed time trend in firms' leverage ratio at IPO. Large proportion of the time trend is still left unexplained. There are other factors affecting capital structure choices. I am now focusing heavily on the demand side when studying capital structure decisions. However, supply side stories should be equally important. For instance, the development of venture capital during the time, or the competitiveness of the credit market (Petersen and Rajan (1995)). These factors should be considered as well in order to fully understand this time trend in corporate leverage ratio. It is also possible that the proxies I use for firm risk and corporate tax rate are noisy. Another route for future research is to look for better measures of these variables.

3.7 Conclusion

In this chapter, I characterize the behavior of firms' leverage ratios at their IPO year. The main results are as follows. First, over time there is a downward time trend in firms' leverage ratio at their IPO year. Second, firms that went public more recently are more adverse to debt financing and deviate more from pecking order behavior. I develop a simple discrete time model to capture the link between firm risk and leverage position. Firm-level risk when going public is able to offer some explanation for my findings. However, the understanding of the observed pattern is still far from conclusive.

Table 3.1 Summary Statistics

	All Firm Years		All Firms at IPO	
Variable	Mean	SD	Mean	SD
Market leverage	0.30	0.24	0.20	0.19
Firm age	16.44	21.16	15.40	20.33
Firm size	4.67	1.80	3.88	1.69
Market-to-book	2.19	2.57	3.33	4.76
Profitability (%)	6.72	21.04	7.61	21.74
Tangibility (%)	25.29	21.93	22.02	21.55
Obs.	46367		5550	

Notes: The table represents variable means and standard deviation for whole sample, and subsample of firm oberservations at the time of IPO.

Table 3.2 The Persistence of Capital Structure

Dep. Var.:	Market Leverage Ratio		
	(1) 5 years after	(2) 10 years after	(3) 20 years after
Initial Leverage Ratio	0.539	0.464	0.305
	(0.025)***	(0.030)***	(0.058)***
Firm size	0.010	0.007	-0.009
	(0.002)***	(0.003)***	(0.005)*
Tangibility	0.001	0.001	0.000
	(0.000)***	(0.000)***	(0.001)
Profitability	-0.002	-0.003	-0.002
	(0.000)***	(0.000)***	(0.001)***
Market -to-Book	-0.045	-0.420	-0.053
	(0.007)***	(0.006)***	(0.013)***
Industry Fixed Effects	Yes	Yes	Yes
R squared	0.485	0.424	0.464
N	3193	1643	274

Notes: These are the result from OLS estimation using robust standard error. The first column is the result for firm year observations that are 5 years after IPO. The second and the third column are the results from observations that are 10 and 20 years after IPO respectively. The industry is defined using Fama-French 10 industries definition.

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

Table 3.3 The Time Trend in CS at IPO

Dep. Var.:	Market Leverage Ratio			
	(1) all	(2) pre-90	(3) post-90	(4) post-80
IPO year	-0.006	-0.004	-0.004	-0.006
	(0.001)***	(0.002)***	(0.001)***	(0.001)***
Firm age	0.001	0.000	0.001	0.001
	(0.000)***	(0.000)	(0.000)***	(0.000)***
Market -to-Book	-0.009	-0.062	-0.008	-0.009
	(0.001)***	(0.006)***	(0.001)***	(0.001)***
Firm size	0.049	0.052	0.044	0.049
	(0.002)***	(0.004)***	(0.002)***	(0.002)***
Tangibility	0.002	0.001	0.002	0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Profitability	-0.002	-0.003	-0.002	-0.002
	(0.000)***	(0.000)***	(0.000)***	(0.000)***
Industry Fixed Effects	Yes	Yes	Yes	Yes
R squared	0.44	0.53	0.43	0.44
N	5550	1516	4034	5417

Notes: These are the result from OLS estimation using robust standard error. The first column is the result from the whole sample. The second and the third column are the results from before and after 1990 subsamples. The fourth column coresponds to post 1980 data. The industry is defined using Fama-French 10 industries definition.

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

Table 3.4 Firms Capital Structure at IPO year across Industries

Specification:	Fama-French Industries								
Dep. Var.:	Market Leverage Ratio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	non-dur	durables	manu	energy	hitech	telecom	shops	healthcare	other
IPO year	-0.0033	-0.0027	-0.0056	-0.0060 ***	-0.0034	-0.0014	-0.0075	-0.0015	-0.0080
	(0.001) **	(0.003)	(0.001) ***	(0.002)	(0.001) ***	(0.002)	(0.001) ***	(0.001) *	(0.001) ***
Firm age	0.000	0.000	0.000	0.000	0.002	0.002	0.001	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000) ***	(0.001) ***	(0.000) ***	(0.000)	(0.000)
Market-to-Book	-0.063	-0.101	-0.047	-0.098	-0.052	-0.052	-0.034	-0.028	-0.023
	(0.008) ***	(0.012) ***	(0.010) ***	(0.014) ***	(0.007) ***	(0.007) ***	(0.007) ***	(0.003) ***	(0.006) ***
Firm Size	0.051	0.056	0.063	0.042	0.027	0.027	0.062	0.023	0.047
	(0.006) ***	(0.010) ***	(0.006) ***	(0.009) ***	(0.008) ***	(0.008) ***	(0.005) ***	(0.003) ***	(0.004) ***
Tangibility	0.001	0.000	0.002	0.001	0.003	0.001	0.000	0.004	0.002
	(0.000)	(0.001)	(0.000) ***	(0.001)	(0.000) ***	(0.001) ***	(0.000)	(0.000) ***	(0.000) ***
Profitability	-0.003	-0.003	-0.004	-0.004	-0.001	-0.002	-0.003	-0.001	-0.003
	(0.001) ***	(0.001) ***	(0.001) ***	(0.001) ***	(0.000) ***	(0.001) ***	(0.001) ***	(0.000) ***	(0.000) ***
R^2	0.513	0.560	0.509	0.454	0.327	0.041	0.460	0.548	0.399
N	301	146	550	166	1861	250	770	683	823

Notes: The industries in each column are: (1) non-durables, (2) durables, (3) manufactoring, (4) Energy, (5) Hitech, (6) Telecom, (7) Shops, (8)Healthcare, (9) Other. The financial and utility industries are excluded.

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

Table 3.5 Debt Issuance After IPO

Dep. Var.:	Change in Long Term Debt	
	(1)	(2)
Financing Deficit	0.236	36.981
	(0.012)***	(3.551)***
IPO year	-0.002	0.000
	(0.000)***	(0.000)*
IPO × Deficit		-0.018
		(0.002)***
Firm age	0.000	0.000
	(0.000)***	(0.000)***
Firm size	0.012	0.012
	(0.001)***	(0.001)***
Tangibility	0.000	0.000
	(0.000)***	(0.000)***
Profitability	0.000	0.000
	(0.000)***	(0.000)***
Market -to-Book	-0.005	-0.005
	(0.001)***	(0.000)***
Industry Fixed Effects	Yes	Yes
R squared	0.19	0.24
N	42512	42512

Notes: These are the result from OLS estimation using standard error robust to both clustering at the firm level and heteroskedasticity. The first column is the result without the interaction term between firm IPO year and financing deficit . The industry is defined using Fama-French 10 industries definition.

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

Table 3.6 The Time Trend in CS with Additional Controls

Control Var.:	Time Trend Coefficient Estimate:			
	(1) All	(2) Pre-90	(3) Post-90	(4) Post 80
None (Baseline)	**-0.006**	**-0.004**	**-0.004**	**-0.006**
Market PE Ratio	**-0.006**	**-0.008**	**-0.004**	**-0.006**
Corporate Tax	**-0.005**	**-0.007**	**-0.004**	**-0.005**
Firm Risk	**-0.006**	-0.003	**-0.004**	**-0.006**
All	**-0.006**	-0.009	**-0.004**	**-0.006**

Notes: These are the coefficient estimates of variable lyear from OLS estimation using robust standard error. The first column is the result from the whole sample. The second and the third column are the results from before and after 1990 subsamples. The foruth column corresponds to post 1980 data. Additional control variables are specified in the first column of each row. All results include standard controls: firm size, profitability, tangibility, market-to-book ratio, IPO year, firm age, and industry dummies.

Bold - significant at 5%

Table 3.7 Firms Capital Structure at IPO year across Industries with Additional Controls

Specification:	Fama-French Industries								
Dep. Var.:	Market Leverage Ratio								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	non-dur	durables	manu	energy	hitech	telecom	shops	healthcare	other
None (Baseline)	**-0.003**	-0.003	**-0.006**	**-0.006**	**-0.003**	-0.001	**-0.007**	-0.001	**-0.008**
Market PE Ratio	-0.005	-0.001	**-0.006**	-0.003	**-0.002**	-0.004	**-0.007**	-0.001	**-0.009**
Corporate Tax	-0.002	-0.003	**-0.005**	-0.003	**-0.004**	0.000	**-0.007**	0.000	**-0.008**
Firm Risk	**0.002**	0.000	**-0.005**	-0.001	**-0.005**	**0.005**	**-0.001**	**-0.003**	**-0.004**
All	**-0.012**	-0.005	-0.003	-0.003	-0.001	**0.007**	**-0.003**	**-0.003**	**-0.007**

Notes: These are coefficient estimates of variable lyear from OLS estimation using robust standard error. Column (1) though (9) present results for each of the Fama-French industries. The financial and utility industries are excluded. Additional control variables are specified in the first column of each row. All results include standard controls: firm size, profitability, tangibility, market-to-book ratio, ipo year, and firm age.

Bold - Significant at 5% level

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