Title
Essays in Finance

Author
Liu, Han

Publication Date
2016

Peer reviewed|Thesis/dissertation

Essays in Finance

By

Han Liu

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

in

Business Administration

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Martin Lettau, Chair
Professor Gustavo Manso
Professor Richard Sloan
Professor Ben Handel

Spring 2016

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Abstract

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The current thesis presents three chapters in finance that investigate how a firm's characteristics affect its internal corporate financing decision as well as the external perception of the firm by the financial market. The paper advances empirical asset pricing by studying how the market's expectations about firms vary systematically with firms' profitabilities and the impact of these expectations on stock prices. Further, the paper adds to corporate finance by investigating new channels through which firms determine their capital structure and compensation contract for their executives.

Previous research indicated that sorting firms by their profitabilities generates sizeable cross-sectional variations in subsequent period stock returns. Firms that have high profitability this period tend to outperform low profitability firms in the next period. The first chapter of this paper investigates whether high profit firms have higher returns because they are fundamentally riskier in some way, or whether mispricing drives the return difference. The chapter presents evidence that the premium associated with profitability is difficult to reconcile with risk-based explanations but is consistent with expectation errors. Firms with a lower profitability prove more volatile, suffer greater drawdowns and are more sensitive to macroeconomic conditions. This means that the profitable firms are actually less risky by most measures and perform better during economic downturns. In addition, a monotonic relationship exists between profitability and forecast error. Stock analysts tend to be overoptimistic for low profitability firms relative to high profitability firms. Surprisingly, this mis-expectation can persist for as long as five years into the future. Furthermore, the profitability premium is mainly concentrated among firms about which the anlysts express the most optimism.

The second chapter, jointly authored with Francesco D'Acunto, Carolin Pflueger and Michael Weber, shows that the frequency with which firms adjust output prices is an important determinant of persistent capital structure. Using restricted BLS data, we constructed a measure of the individual firm's output price rigidity and matched it with financial information of the firm. Flexible-price firms choose higher financial leverage than inflexible-price firms, controlling for known determinants of capital structure. We rationalize this novel fact using a costly-state-verification model, where inflexible-price firms are more exposed to aggregate shocks, and hence face tighter financial constraints. The model predicts that bank lending, by providing monitoring, relaxes financial constraints and narrows the leverage gap between inflexible- and flexible-price firms. Consistent with model predictions, we show that inflexible-price firms increased leverage more than did flexible-price firms following the staggered implementation of the 1994 repeal of interstate bank branching regulations. Firms' frequency of price adjustment did not change around this deregulation, supporting a causal interpretation of price flexibility on corporate leverage.

In the third chapter of the dissertation, I investigate the role that innovation plays in executive compensation. Agency-based theory of optimal executive compensation literature has long puzzled over the empirical observation that executives are being compensated for industry performances that are outside the executive's control. Using patent-based metrics as the measure of innovativeness, I show that this "pay for luck" phenomenon is mainly concentrated among the most innovative firms and is stronger for firms in more innovative industries. I conjecture that motivating innovation might require a different contract design,and in some cases, "pay for luck" might actually be optimal in incentivizing experimentation.

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Acknowledgements

I am deeply grateful for the support that my dissertation chair Martin Lettau, and committee members Gustavo Manso, Richard Sloan and Ben Handel have given me. Martin and Richard have been extremely helpful in providing research directions and valuable comments that improved the dissertation tremendously. Gustavo has been a great mentor and a good friend. As always, Ben has been generous with his time.

I would like to give special thanks to Farshad Haghpanah and Xinxin Wang. They have always been there for me, and have believed in me even when I did not. I would also like to thank my classmates Carlos Avenancio, Albert Hu, Sheisha Kulkarni, Sanket Korgaonkar, and Calvin Zhang. The past five years have been full of ups and downs, and I could not have done it without their support and friendship.

Finally, I would like to express my gratitude to my past classmates Francesco D'Acunto and Michael Weber. They have been role models for me and their passion for research is truly inspiring.

CHAPTER 1

Profitability Premium: Risk or Mispricing?

1.1. Introduction

Previous research has shown that a firm's profitability exhibits a strong link with the firm's expected stock return and predicts return as far as 10 years ahead. The return variations generated by sorting based on profitability are not subsumed by the size and book-to-market factors. Moreover, a factor constructed based on profitability has been shown to explain a wide range of asset pricing "anomalies"[1]. The current paper studies the behavior of the premium associated with profitability and tries to understand what is driving this premium.

Researchers have traditionally divided into two camps regarding why some groups of firms yield superior returns relative to other firms. Profitable firms' stock might perform better because it is fundamentally riskier, leading investors to demand a higher risk premium for holding these stocks. Alternatively, the profitable firms might have higher return because these firms are mispriced due to incorrect expectation of the market. The mis-expectation might result from a myriad of cognitive biases to which investors are subjected. For example, they might extrapolate past performance or earnings too far into the future. They might overreact to good or bad news, and as a result, tend to overbuy those that have performed well in the past (glamour stocks) and oversell those that have performed poorly. These two potential explanations have different implications for both academic research and industry applications. If the premium is truly driven by fundamental risk, then profitability should be incorporated into a benchmark model of return. This benchmark model can be used to better discount cash flows in capital budgeting applications and to test for alphas of new strategies and proposed factors. It can also be used to evaluate portfolio returns and fund performance. If the premium is just mispricing, market participants will eventually catch on to it. This implies that the premium will disappear in the future as more investors begin trading based on this idea.

The analysis in the current paper is divided into two parts. In the first part, I investigate whether the profitability premium is due to systematic risk. I examine various measures that are traditionally associated with risk across 10 portfolios sorted based on profitability. The profitable firms have quite consistently outperformed the unprofitable firms. They also tend to have a lower return volatility, leading to a higher Sharpe ratio. Moreover, these firms have a lower drawdown in times of distress. Next, I decompose the beta of the portfolios with respect to the market into a component associated with cash flow news and a component associated with discount rate news. Campbell and Vuolteenaho (2004) argue that cash flow news only changes the wealth of the investors without affecting the investment opportunity set, while discount rate news affects both the wealth and the investment opportunity set. In an intertemporal asset pricing model, the cash flow news would have a higher price of risk

[1] See Novy-Marx (2013) and Ball et al. (2015)

since its effect is more permanent while the discount rate news provides a hedge component because of changing investment opportunity. A risk-averse, long-term investor would demand a higher premium for holding assets that covary with a market's cash flow news than for holding assets that covary with a market's discount rate news. Therefore a firm's risk will depend not only on its overall market beta, but also on the composition of the beta with respect to cash flow (co-movement with market cash flow news) and discount rate beta (co-movement with the market discount rate news). Profitable firms might be riskier if they have higher covariations with the market's cash flow news, that is, higher cash flow beta. This is plausible since profitability is essentially a measure of how much money the firm can generate and how consistently they can generate that money. However, I find that unprofitable firms actually have higher cash flow beta relative to the profitable firms.

Economic theory suggests another way that the profitable firms can be riskier. Investors care the most about returns during bad times when their marginal utility of wealth is high. While the profitable firms have higher unconditional returns, investors might still avoid them if their returns are the lowest exactly during bad times. Stated in another way, the unprofitable firms might yield lower returns if they perform well in bad times, thereby providing a hedge to the investors. To study this possibility, I lexamine the cyclical variation of the premium across the business cycle and how the premium relates to common macroeconomic predictors of return. I find that the premium is actually higher during economic downturns. Thus the profitable firms perform even better than do the unprofitable firms during bad times when the marginal utility is the highest. Further, to more accurately capture the asymmetry in return behavior of profitable and unprofitable firms across the business cycle, I adopt a two-state Markov-switching model that allows the conditional distribution of returns to vary with the state of the economy. This flexible econometric framework gives additional insights on the mechanisms generating the difference in expected returns. The expected profitability premium exhibits clear cyclical variations with a tendency to spike up at the beginning of recessions. Across the states, the unprofitable firms display the highest degree of asymmetry in their sensitivity to aggregate economic conditions.

In the second part of the paper, I investigate the mispricing hypothesis by examining the expectation error of the market participants. Specifically, I examine the difference between the earnings forecasted by sell-side analysts and the actual earnings realized across profitability-sorted portfolios. If the low return of the unprofitable firms relative to the profitable firms is due to investors being too optimistic about its future performance, I should find that the difference between forecast and actual earnings (expectation error) is larger for unprofitable firms than for profitable firms. The results indicate that a monotonically decreasing relationship does exist across the 10 deciles of profitability from low to high. The expectation error is larger for the unprofitable firms. Interestingly, this expectation error is quite persistent and lasts for up to five years into the future. I also analyze potential reasons leading to the expectation error. Unlike the typical behavioral explanation given for the value premium in which the growth firms tend to be "glamorous" stocks that have performed well in the past and the investors naively expect to continue doing well, the unprofitable firms have actually performed poorly over the few year prior to portfolio formation. Rather it is the profitable firms that have done well in the past, and they tend to continue perform well during the one year following the portfolio formation. They also tend to be bigger firms with higher earnings yield, higher asset growth, lower stock issuance and lower distress. Overall, the investors seem to expect the performance of the profitable firms to mean-revert more quickly than they actually do, and they are willing to bet on the revival of the unprofitable firms despite low net income and poor current performance.

My paper relates to the literature on the role of profitability in determining stock return. Early papers such as Ball and Brown (1968) focus on accounting earnings and show that net income predicts the cross section of returns. However, later research by Fama and French (1992) and Fama and French (1996) show that information contained in earnings is completely subsumed by size and book-to-market. More recently, there has been a revival of interest in the link between profitability and stock return that relies on different measures. Novy-Marx (2013) argues that gross profitability (GP), defined as revenue minus cost of goods sold divided by book value of total assets, provides a cleaner measure of true economic profitability than earnings. This is because accounting earnings also captures investment expenses such as research and development (R&D), that actually help increase future economic profit. A firm that is spending a high amount on R&D might have high future profitability, but low current earnings. He shows evidence that GP provides incremental information above size and book-to-market and works especially well when combined with the value signal. His results have attracted considerable attention both from academia and from industry. Some asset managers reported that they changed their investment strategies based on results. More importantly from an academic's perspective, Novy-Marx shows that a GP factor can explain a large set of asset pricing anomalies. Building on Novy-Marx's work, Ball et al. (2015) examine profitability closer and construct an alternative measure, operating profitability, that exhibits an even stronger link with firm performance than gross profitability. Given the robust explanatory power of profitability beyond size and value and its relation with the other asset pricing anomalies, Fama and French (2014) try to incorporate profitability as an additional factor that summarizes the heterogeneity in stock returns. In a similar line of research, Hou et al. (2014), motivated by the q-theory of investment, propose an alternative factor model for determining the cross-section of expected returns consisting of a market factor, a size factor, an investment factor, and a profitability factor and show that it outperforms the Fama-French 3-Factor model. Additionally, the current paper fits into the large literature in using behavioral biases to explaining the cross section of stock returns. Early contributions such as Lakonishok et al. (1994) and La Porta (1996) focus on the value premium. A survey of this line of study can be found in Barberis and Thaler (2003). More recently, Engelberg et al. (2015) aggregated 97 stock return anomalies and investigate the earnings announcement period returns and analyst forecast errors. They find that the returns are much higher around announcement periods. In addition, the anomaly signals predict the forecast error. Their work suggests that some kind of expectation error might be driving these anomalies. However since all of the predictors are aggregated, the results are in a black box, making it difficult to distinguish exactly what anomalies are driving the results, or to determine the relative importance of expectation error across the anomalies. My paper is also closely related to Wang and Yu (2013). They explore various forms of conditional portfolio sorting and show that the premium exists primarily among firms with high uncertainty and information cost. Moreover, they argue that since the there is little evidence of long-run reversals, the premium is likely to be driven by underreaction. My paper differs from theirs along several dimensions. My main measure of profitability is different from theirs and has been shown to provide a stronger link with expected returns. My econometric framework is also more flexible and allows me to better capture non-linear effects. Most importantly, I directly show the expectation error across firms with different profitability and argue that the lack of long-run reversal might be driven by the fact that the investors have not been paying attention to these newer measures.

1.2. Data and Profitability Measure

The stock return data is obtained from the Center for Research in Security Prices (CRSP). I only include ordinary common shares traded on NYSE, Amex, and NASDAQ. I combine that with firm level financial information from the Standard and Poor's Compustat database. The portfolios are constructed based on quintile and decile sorts using the New York Stock Exchange (NYSE) breakpoints. As is standard in the literature, the portfolios are value-weighted and rebalanced each year at the end of June. The accounting data for all fiscal years ending in calendar year $t-1$ are matched to the returns for the period from July of year t to June of year $t+1$. The sample consists of firms that have a non-missing market value of equity and book-to-market. Following most of the papers in the literature, I exclude the financial firms that have a one-digit standard industrial classification code of six.

Profitability is meant to measure the productiveness of the firm's capital in generating cash flow. While the conceptual idea of profitability is clear, the literature has used various definitions and items in the financial statements in the past to capture it. Fama and French (2006) motivate their empirical analysis using the clean surplus accounting and define profitability to be net income divided by the book value of equity. Wang and Yu (2013) and Hou et al. (2014) use return-on-equity (ROE) as their main measure of profitability, defined as income before extraordinary items (Compustat item IB) divided by book equity. A recent paper by Novy-Marx (2013) that has received a lot of attention in both academia and industry argues that true economic profitability becomes more polluted the further down the income statement one goes. Furthermore, scaling the income items by book value of equity risks conflating firm's capital productivity with book-to-market which is related to the cross-section of stock returns. He advocates gross profitability, defined as the ratio of revenue minus cost of goods sold over total asset, and shows that portfolios sorted on this measure exhibit significant variations in return and is not explained by the usual Fama-French 3-Factor model.

For the purpose of this study, I will mainly focus on an even more refined measure of profitability as given in Ball et al. (2015)

$$Profitability = \frac{REVT - COGS - (XSGA - XRD)}{AT} \tag{1.2.1}$$

where $REVT$ is the total revenue, $COGS$ is the cost of goods sold, $XSGA$ is the selling, general & administrative expense, XRD is the R&D expense and AT is total asset. Ball et al. (2015) argue that this measure, which they refer to as operating profitability, better matches current expenses with current revenues and leads to a significantly better predictor of future returns than the gross profitability measure. It differs from GP in that it includes the selling, general & administrative expense which Ball et al. (2015) show has similar covariance with future return as the cost of goods sold. The R&D expenses are subtracted away because Compustat defines selling, general & administrative expense as the sum of firms' actual selling, general & administrative expense and their R&D expense. Since R&D expenses not only reduce current profit but also generates future revenues, undoing Compustat's adjustment leads to a cleaner measure of profitability. For robustness, I have also repeated the estimations using gross profitability. For all the subsequent results that follow, using gross profitability will not make a material difference to the conclusions.

I take the analysts' earnings forecast and expected growth rates from the Institutional-Brokers-Estimates-System (IBES) in the WRDS database. While not a perfect proxy for the expectation of market participants, these forecast and the accompanying reports are used by institutional investors in their decision making process and provides a valuable guide to how these investors think. Moreover, the techniques used to come to these conclusions are standard among market participants and should be correlated with their unobserved belief. The IBES data aggregates the earnings and growth forecasts issued by sell-side stock analysts. For each firm-year, I consider the mean analyst forecast of earnings. Since the earnings forecasts are issued multiple times in a year, I only keep the closest forecast just prior to portfolio formation in July of year t and that the forecast end period will fall between July of year t to June of year $t+1$.

1.3. Are Profitable Firms Riskier?

Broadly speaking, there are two interpretations to the explanatory power behind the cross-sectional determinants of stock return such as book-to-market, size etc. The first interpretation argues that the additional risk that value and small firms incur drives the additional return that they get on average. The alternative explanation argues that investors fail to fully understand the relationship between these financial variables and subsequent future performances, and therefore they form erroneous expectations. The profitability premium is also subject to these two interpretations. In this section, I will analyze whether profitability premium is consistent with risk-based explanations. There are two ways in which the profitable firms can be riskier than the unprofitable firms. First, the profitable firms have to underperform in some states of the world. Second, the states that they underperform in are the "bad" states in which the marginal utility of wealth is high.

Traditional Risk Analysis. I begin by examining the performance of profitable firms and unprofitable firms over time and ask whether the underperformance remains consistent. Figure 1 shows the return of high profitability firms relative to low profitability firms on a year by year basis from July 1963 to December 2013, with the first and last year only accounting for six months of return each. The premium is calculated as the difference between the value-weighted return of firms in decile 10 of profitability minus that of decile 1.

The plot shows that profitable firms have outperformed unprofitable firms in 37 out of the 51 years in the sample. One possible explanation for such high percentage of outperformance that is consistent with systematic risk is that the premium takes the stairs up but the elevator down. That is, it is subject to a "rare disaster" shock that leads to extremely low returns. In the years of underperformance, the lowest return is -34%. This is lower than the highest return of 41% among the years of outperformance. The average return difference in the 37 years of outperformance is 10.8% while the average return difference in the 14 years that profitable firms underperform is 11.4%. Thus, while profitable firms consistently yield higher returns than unprofitable firms, the few instances in which they underperform do not lead to significantly higher negative returns.

Next, I examine a set of important factors typically connected to high risk premia. Panel A of Table 1.5.1 shows the results. I begin by looking at the returns and volatility of each of the portfolios across a variety of holding periods, ranging from one month to five years. Across all holding periods, profitable firms earn higher returns than unprofitable firms The portfolio with the lowest profitability has the highest annualized standard deviation of 0.236 while the other portfolios have roughly the same standard deviation of 0.17. Volatility therefore cannot be a driver of the greater risk of the profitable firms under the risk hypothesis. Indeed the firms with lower volatility actually have higher average returns. Not surprisingly, the Sharpe ratio is the lowest at 0.084 for the lowest decile of profitability, and it increases to above 0.4 for the high profitable firms in the top three deciles. The next several rows display the downside risk of the portfolios in more detail. One possibility for the high return of the profitable firms is that they might experience periods of enormous loss, and investors must be given a return premium in order to induce them to hold these stocks. Yet again the results do not seem to align with this hypothesis. I investigate the maximum drawdown, defined as the return from peak to trough, for holding periods of three months, six months, one year, and two years. In all cases, the low profitable firms tend to suffer significantly higher drawdowns and without exception, the lowest decile of profitability suffers the worst drawdown. For example, the worst three-month drawdown for the lowest decile of profitability is -51% while the next highest drawdown is suffered by decile 3 at -37%. The worst one year drawdown for the lowest profitability decile is -74%. This is more than 20% lower than any of the other portfolios and almost 30% lower than the most profitable decile.

Previous research has shown that the profitability premium is not subsumed by the Fama-French 3-Factor model; therefore it is not explained by CAPM. However, Campbell and Vuolteenaho (2004) have shown that the return on the market portfolio can be decomposed into news about future discount rate and news about future cash flow. In the first case, the wealth decreases but future investment opportunities improve while in the second case, wealth decreases and future investment opportunities remain unchanged. Therefore these two components should affect risk premium in different ways. Specifically, the beta with respect to the market can be broken down into a discount rate beta and a cash flow beta. Firms with higher cash flow beta relative to discount rate beta would be riskier since their covariation is with cash flow news that does not affect investment opportunity set, even though they might have similar overall CAPM beta.

Panel B of Table 1.5.1 shows the relative make up of the betas across the profitability portfolios. I follow the procedure outlined by Campbell and Vuolteenaho (2004). On average the low profitability firms tend to have higher overall beta than the high profitability firms. In particular, the decile 1 portfolio has both substantially higher discount rate beta and cash flow beta than any of the other portfolios. Thus CAPM beta cannot explain the low returns of the low profit firms. More importantly, the relative weight of discount rate and cash flow beta cannot explain the variation in returns either. Decile 1 has a discount rate beta of 0.676 and a cash flow beta of 0.792, so the proportion of cash flow beta relative to the total beta is 54%. By comparison, the most profitable decile 10 has a discount rate beta of 0.585 and a cash flow beta of 0.499 so that cash flow beta only makes up 46% of the total beta. Thus high profitability firms not only have lower total beta, but also lower proportion of cash flow beta. One caveat to the results is that beta decomposition has been shown to be very sensitive to model specification (see Chen and Zhao (2009)). This is because the cash flow news is usually back out as a residual after directly measuring the discount rate new; therefore it captures a great deal of modeling noise. My results do not preclude the possibility that profitable firms indeed have high cash flow beta but the VAR model that I used is misspecified.

Business Cycle Variations. In this section, I empirically analyze the time variation in the profitability premium and relate it to several well-known macroeconomic variables. I examine the data using the traditional regression approach to investigate whether the correlation between conditioning variables and future stock return exhibit systematic patterns across different profitability portfolios. In addition, I adopt a more flexible econometric model that allows me to capture asymmetric response of profitable and unprofitable firms' stock return to business conditions.

The discussion at the beginning of this section suggests that profitable firms are consistently outperforming unprofitable firms with lower volatility and lower drawdown. However, this does not automatically imply that profitable firms are less risky. Economic theory suggests that the riskier firms are those that tend to underperform in bad times when the marginal utility of consumption is high, even if they have a higher return unconditionally. I start off by analyzing the correlation of the relative return of profitable and unprofitable firms with respect to the aggregate market. Figure 1.5.2 plots the 12-month moving average of profitability premium (return of the most profitable decile minus return of the least profitable decile) along with the 12-months moving average of aggregate market return given by the CRSP value-weighted index. The NBER recessions are shaded.

The figure shows a clear negative relationship between the profitability premium and market return. During market downturns prior to the onset of recessions, the profitability premium tends to spike up, driven mainly by the low return of the unprofitable firms. The most notable exception is the 1973-1975 recession with its stagflation exacerbated by the oil crisis. Qualitatively, the relationship becomes more reliable after the 1980s. In the two most recent recessions, the aggregate market loss is accompanied by sharp upward spike in the profitability premium.

To understand the premium and how it changes through the business cycle, Table 1.5.2 shows some summary statistics and correlations of the premium related to value, size, and profitability.

The size premium is significantly higher in recessions than in expansions, in agreement with the results of Perez-Quiros and Timmermann (2000). They argue that smaller firms are more susceptible to credit constraints and this constraint is especially likely to bind during bad economic times. Therefore, the expected return on small firms relative to large firms should be higher during recessionary states. The size premium also has a significant 32 percent correlation with the aggregate market return. The profitability premium displays some difference across the recessionary and expansionary states. The premium during recession of 0.69 percent is almost twice the premium during expansion of 0.36 percent. Interestingly, it also quite a significant raw negative correlation with the market of -33.4 percent, on par with the correlation associated with the size premium. Finally, the value premium displays less cyclicality with the difference between recession and expansion being only 0.1 percent. The raw correlation with the market of -4.9 percent is also much less compared to size premium and profitability premium. This is consistent with the results in Chen et al. (2008) that the expected value premium is only weakly countercyclical.

Looking now at the correlation of the portfolios' return with aggregate macroeconomic variables in the tradition of Fama and French (1989). Fama and French (1989) explore the expected return on different stock and bond portfolios and their correlations with aggregate conditioning variables by running predictive regressions of the portfolio returns on the conditioning variables for various horizons. Table 1.5.3 displays the regressions of the profitability decile portfolios' excess return on a constant, the one-month Treasury bill (T-Bill) rate, the default spread, and the dividend yield. The Newey-West standard errors adjusting for overlapping returns are reported in parentheses.

The one-month Treasury bill rate I_t is widely used to proxy for the investors' unobserved expectation of future economic activity. Fama (1981) shows that a higher nominal T-Bill rate is indicative of an unobserved negative shock to real economic growth. Moreover, the Federal Reserve routinely lowers short term interest rate to stimulate growth in anticipation of economic downturns, leading many studies such as Fama and Schwert (1977), Campbell (1987), and Whitelaw (1994) to use it as a regressor in stock return predictions. These studies typically find a negative correlation between interest rate and future stock returns. More importantly for our study, interest rate serves as a proxy for firm's cost of debt capital and fluctuates as aggregate credit condition changes.

In agreement with the results of long horizon regression studies such as Campbell and Shiller (1988) and Hodrick (1992), the point estimates of the T-Bill coefficients become more negative and the p-value increases as the horizon of returns progresses from 1 month to 12 months. This is also a general result that holds for default spread and dividend yield. The previous studies interpret this as more predictability of stock return at longer horizons. More interestingly, the point estimate of the Treasury bill coefficient increases from the low profitability deciles to the high profitability decile. This suggests that stocks in the low profitability decile are much more sensitive than those in the high profitability decile to fluctuations in general economic conditions and credit market conditions. Moreover as the horizon increases, the magnitude of the difference in the coefficients also increases. For a 1-month return, the point estimate on the T-Bill is -6.03 for the least profitable portfolio and -2.99 for the most profitable portfolio. Thus the least profitable portfolio's coefficient is approximately twice that of the most profitable portfolio. This difference increases monotonically with the regression horizon. For 12-month return regressions, the point estimate on the least profitable portfolio is -54.47 while the same estimate for the most profitable portfolio is -15.46, increasing by a factor of three or four. Thus if we consider returns over longer periods of time, the association between economic growth and return of unprofitable firms becomes even stronger relative to the association between economic growth and return of profitable firms. This provides another perspective to the findings in Novy-Marx (2013) and Ball et al. (2015) that the profitability premium is persistent. Part of the persistence might stem from the correlation between economic growth and long-term future return.

The default premium Def_t is given by the difference between the Moody's Aaa yield and Baa yield obtained from the St. Louis Federal Reserve database. Empirical macroeconomic research such as Stock and Watson (1989) has shown that default premium is one of the strongest business cycle forecasters. In stock return forecast, researchers as early as Keim and Stambaugh (1986) have found that default premium is positively correlated with future stock returns. Jagannathan and Wang (1996)'s study on conditional CAPM uses the default spread as the only conditioning variable. During bad times, investors will prefer bonds with more stable payout and lower default risk, thus widening the gap between the yield an investor can earn from a security with more credit risk relative to one with less credit risk. This variable captures the general credit constraintness of the economy. Unprofitable firms more affected by distress risk should be more sensitive to aggregate credit constraintness compared to profitable firms.

The results agree broadly with our intuition. In general, stock return of firms with low profitability is more sensitive to the default spread than the stock return of high profitability. For 1 month returns, the coefficient of lowest profitability portfolio's return on default premium is 0.67, which is about twice the coefficient of the highest profitability portfolio of 0.31. Again, this difference tends to increase with horizon. For the 12-month return regressions, the coefficient on the default premium is four times greater in the tenth decile than in the first decile.

Finally, I include the aggregate dividend yield, as defined by the sum of the previous 12 months' dividends of the value-weighted CRSP index divided by the current level of the index. A high dividend yield indicates high discount rate and thus it is meant to capture the time variation in the aggregate risk premium. Most classic studies such as Campbell and Shiller (1988) and Fama and French (1988) include it in modeling expected stock returns. The pattern of the coefficient estimates are qualitatively similar to the Treasury bill and the default spread. Increasing the horizon in general increases the magnitude and statistical significance of the coefficients. The lowest profitability decile' stock returns are more sensitive to the dividend yield than the stock return of the highest profitability decile by a factor of about two. This ratio also increases as the prediction horizon increases, albeit not as much compared to the coefficients on the T-Bill and default premium.

Overall, the results suggest a clear cyclical fluctuation in the profitability premium. The premium tend to increase during recessions and when the aggregate market is performing poorly. This is because the low profitability firms' stock returns are more sensitive to aggregate risk premium, economic growth and credit market conditions than the stock returns of the profitable firms. Low profit firms' returns tend to decrease more during economic downturns than that of the high profit firms. This increases the difference between the two groups of firms, and leads to an upward spike in the profitability premium. Thus the unprofitable firms perform worse in harsh economic times when the marginal utility is high, so their low return cannot be explained away as a hedge for recessions. Building on the suggestive evidence in this part, I next explicitly model the divergent response of the portfolios' stock returns across different states of nature.

While the regressions noted in the previous section provide insight about the differential response of profitability portfolios to aggregate market conditions, they cannot capture asymmetric response of the stock returns across recessions and expansions. This is important for a full investigation of risk-based explanations. We have shown that the unprofitable firms have the same correlation structure as the profitable firms with respect to the macroeconomic variables but are unconditionally more sensitive. This does not automatically rule out the possibility that these unprofitable firms provide a hedge for bad times. For example if a firm's correlation with macro conditions changes during economic downturns, it can still be attractive for investors to hold these firms in their portfolios. In this section, I use the nonlinear Markov switching model to investigate the time variations in the expected stock return of profitable and unprofitable firms and their relation to macroeconomic variables across different states of the economy. This model was originally developed by Hamilton (1989) to investigate the fluctuation of macroeconomic variables through the business cycle, and has been used by Hamilton and Lin (1996) to study time variations in stock return and volatility. Later, Gray (1996) further extended the model to include time-varying transition probability. Perez-Quiros and Timmermann (2000) utilize the model to investigate the relationship between firm size and cyclical stock return. In a similar paper, Gulen et al. (2011) applies the same framework to study cyclical variations and predictability of the value premium.

I will most closely follow the model of Perez-Quiros and Timmermann (2000) in my investigation. For simplicity there will be two states with the identity of the state determined by data. Let ρ_t denote the portfolio's excess return in period t. Let $\mathbf{X}_{t-1}$ be a vector of conditioning variables. I allow the intercept, slope coefficients and volatility of the excess returns to be a function of the latent state variable given by S_t

$$\rho_t = \beta_{0,S_t} + \boldsymbol{\beta}'_{S_t}\mathbf{X}_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2_{S_t}) \tag{1.3.1}$$

With two states, the latent variable S_t will take on values 1 and 2. The coefficients and variances will be either $(\beta_{0,1}, \boldsymbol{\beta}'_1, \sigma^2_1)$ or $(\beta_{0,2}, \boldsymbol{\beta}'_2, \sigma^2_2)$.

The state transition probabilities follow a first-order Markov Chain

$$\begin{aligned} p_t &= P(S_t = 1|S_{t-1} = 1, \mathbf{Y}_{t-1}) = p(\mathbf{Y}_{t-1}) \\ 1 - p_t &= P(S_t = 2|S_{t-1} = 1, \mathbf{Y}_{t-1}) = 1 - p(\mathbf{Y}_{t-1}) \\ q_t &= P(S_t = 2|S_{t-1} = 2, \mathbf{Y}_{t-1}) = q(\mathbf{Y}_{t-1}) \\ 1 - q_t &= P(S_t = 1|S_{t-1} = 2, \mathbf{Y}_{t-1}) = 1 - q(\mathbf{Y}_{t-1}) \end{aligned}$$

The conditioning vector Y_{t-1} is known at $t-1$ and affects the state transition probability between time $t-1$ and t.

I follow Filardo (1994) in allowing the state transition probability to be time-varying and dependent on the economic leading indicator. This allows the model to capture the change in investor's information about the transition probabilities. The transition probabilities are as follows

$$\begin{aligned} p^i_t &= P(S^i_t = 1|S^i_{t-1} = 1, \mathbf{Y}_{t-1}) = \Phi(\gamma^i_1 + \gamma^i_2 \triangle CLI_{t-2}) \\ q^i_t &= P(S^i_t = 2|S^i_{t-1} = 2, \mathbf{Y}_{t-1}) = \Phi(\pi^i_1 + \pi^i_2 \triangle CLI_{t-2}) \end{aligned}$$

The variable $\triangle CLI_{t-2}$ is the year-on-year log-difference in the Composite Leading Indicator obtained from the OECD database, lagged two months to account for delayed data release. The function $\Phi(\cdot)$ is the cumulative density function of a standard normal random variable.

Given the assumptions about the normality of the innovation ε_t, the estimation of the parameters is performed via the maximum likelihood method. Let $\boldsymbol{\theta}$ denote the vector of parameters, and Ω_{t-1} denote the information set at time $t-1$ that includes $\mathbf{X}_{t-1}$, ρ_{t-1}, $\mathbf{Y}_{t-1}$ and all of these variables' values prior to time $t-1$. Then the density conditional on being state j is given by

$$f(\rho_t|\Omega_{t-1}, S_t = j; \boldsymbol{\theta}) = \frac{1}{\sqrt{2\pi\sigma_j}} exp \left(\frac{-(\rho_t - \beta_{0,j} - \boldsymbol{\beta}'_j\mathbf{X}_{t-1})^2}{2\sigma_j} \right) \tag{1.3.2}$$

The log-likelihood function is given by

$$\mathcal{L}(\rho_t|\Omega_{t-1};\boldsymbol{\theta}) = \sum_{t=1}^{T} log(\phi(\rho_t|\Omega_{t-1};\boldsymbol{\theta})) \tag{1.3.3}$$

The density $\phi(\rho_t|\Omega_{t-1};\theta)$ is calculated by summing the probability-weighted state densities $f(\cdot)$ across the two possible states

$$\phi(\rho_t|\Omega_{t-1};\boldsymbol{\theta}) = \sum_{j=1}^{2} f(\rho_t|\Omega_{t-1}, S_t = j;\boldsymbol{\theta})P(S_t = j|\Omega_{t-1};\boldsymbol{\theta}) \tag{1.3.4}$$

where $P(S_t = j|\Omega_{t-1};\boldsymbol{\theta})$ is the conditional probability of being in state j at time t given the conditioning information at time $t-1$.

The conditional state probabilities can be obtained recursively from the total probability theorem

$$P(S_t = i|\Omega_{t-1};\boldsymbol{\theta}) = \sum_{j=1}^{2} P(S_t = i|S_{t-1} = j, \Omega_{t-1};\boldsymbol{\theta})P(S_{t-1} = j|\Omega_{t-1};\boldsymbol{\theta}) \tag{1.3.5}$$

The conditional state probabilities can be calculated from Baye's Rule

$$P(S_{t-1} = j|\Omega_{t-1};\boldsymbol{\theta}) = \frac{f(\rho_{t-1}|\mathbf{X}_{t-1}, \mathbf{Y}_{t-1}, \Omega_{t-2}, S_{t-1} = j;\boldsymbol{\theta})P(S_{t-1} = j|\mathbf{X}_{t-1}, \mathbf{Y}_{t-1}, \Omega_{t-2};\boldsymbol{\theta})}{\sum_{j=1}^{2} f(\rho_{t-1}|\mathbf{X}_{t-1}, \mathbf{Y}_{t-1}, \Omega_{t-2}, S_{t-1} = j;\boldsymbol{\theta})P(S_{t-1} = j|\mathbf{X}_{t-1}, \mathbf{Y}_{t-1}, \Omega_{t-2};\boldsymbol{\theta})} \tag{1.3.6}$$

The parameters can be estimated via a recursive iteration between the two conditional state probabilities. The specific implementation is done using the Markov Regime Switching Models package in Matlab written by Perlin (2014), with an augmentation by Ding (2012) that allows for time varying transition probabilities.

For each profitability decile indexed by i, we estimate a separate model with the excess return of each of the portfolios being dependent on an intercept term, lagged values of the one-month T-Bill rate, a default premium, and the aggregate dividend yield. This specification include the common regressors in the literature on stock predictability. The equation that we estimate is thus

$$\rho_t^i = \beta_{0,S_t}^i + \beta_{1,S_t}^i I_{t-1} + \beta_{2,S_t}^i Def_{t-1} + \beta_{3,S_t}^i Div_{t-1} + \varepsilon_t^i \tag{1.3.7}$$

where $\varepsilon_t \sim N(0, \sigma_{S_t}^2)$.

The one-month Treasury bill rate I_t, the default premium Def_t and the aggregate dividend yield Div_t are common predictors in stock return regressions and are all described in Section 3.2. Unlike in Section 3.2, the goal here is to understand the asymmetric response of each of the portfolios return across economic expansions and downturns. That is, we want to study any differences in loading across recessionary and expansionary for profitable and unprofitable firms, both in sign and in magnitude.

Table 1.5.4 reports the coefficients estimated by fitting the Markov switching model for each of the 10 profitability-sorted portfolios. The table also reports the standard errors of the estimates, estimates of the variance in each states and the overall log likelihood of fit for the model. The variance estimates clearly indicate that State 1 is the low volatility state and State 2 is the high volatility state. It is tempting to interpret this as saying that State 1 correspond to economic expansion and State 2 correspond to recession. Before we can make this conclusion, it helps first to understand the states of the economy that the models identified through the latent approach. Figure 1.5.3 plots the model-estimated conditional probability of being in the high volatility state given the information in the previous period. The top plot shows the model-fitted probability estimated from the highest decile of profitability while the bottom plot shows the same probability estimated from the lowest decile of profitability. The recessions identified by the NBER are shaded.

The estimated probabilities are similar regardless of whether we use decile 1 or decile 10 of the profitability portfolio. The figure shows that the high volatility state picks up both the recessionary states as well as times of exceedingly high equity market volatility. It also underlies the danger of hastily concluding that high volatility state is the same as recessionary state. There are several periods of high stock volatility that does not lead to recession. The two most obvious examples are the October 1987 stock crash, and the Asian Financial Crisis of 1997. The model identifies those periods as being in the high volatility state. Similarly, the recession of the early 1980s are not recognized as being a state of high volatility. Overall however, the state probabilities do display a strong relationship with the business cycle. Thus from now, I will interchangeably refer to the high volatility State 2 as recessionary states, and the low volatility State 1 as expansionary states.

Keeping in mind the caveats regarding the states identified by the model, I can now examine the estimated coefficients from the model. I focus first on the volatility estimates. These parameters have very small standard errors, suggesting that they are quite precisely estimated. As noted previously, the high volatitlity states are usually also the recessionary states, consistent with evidence given in Schwert (1989). More interestingly, the coefficients show that the return volatility decreases in profitability, and this effect is stronger during the high volatility states. During expansions, the volatility estimate for the low profitability portfolio is 0.0022 and the volatility estimate of the high profitability portfolio is 0.0015. The difference is only 0.0007. During recessions, however, the difference between the low profitability portfolio of 0.021 and the high profitability portfolio of 0.006 is 0.015. This is more than 20 times the difference during expansions. Thus the volatility of the unprofitable firms are more strongly influenced by aggregate economic condition than that of the profitable firms.

Consider now the mean equation. Since the recessionary states are much less common than expansionary states, these estimates are much less precise and none of the estimates for recessionary states are statistically significant. I focus first on the coefficients on the Treasury bill. Consistent with the results in Section 3.2, I find that the low profitability portfolio is more sensitive to interest rate than the high profitability portfolio and that the point estimates of the coefficients are all negative. The flexible econometric specification allows me to extend the previous finding in two ways. First, note that during recessions, the sensitivity of the return with respect to the interest rate is flipped from negative to positive. This holds true for 9 of the 10 profitability portfolios. The absolute magnitude of the estimates is roughly the same as during expansions. Secondly, the difference in sensitivity between expansion and recession is much higher for the low profitability firms than the high profitability firms. For decile 1, the difference in interest rate coefficient between expansion and recession is 14.46 while the same difference for decile 10 is only 8.12.

I turn now to the coefficients on default premium. Most of the coefficients are negative for the recessionary states but they are all statistically insignificant. The positive coefficients estimated for expansionary states are mostly statistically significant and positive as in the simple linear model. However, the coefficients do not show a clear pattern across the portfolios. During recessions, the difference in point estimates is greater than during expansions. The general conclusion is that the default premium's positive correlation with the return is only precisely estimated in periods of economic expansions, and if there is indeed a negative relationship between profitability and sensitivity with the default premium as suggested by the results in Section 3.2, it might primarily be driven by recessionary periods.

Finally, the coefficients on the dividend yield across the deciles are qualitatively similar to that of the interest rate. They have mostly positive point estimates and tend to decrease in magnitude as profitability increases, so the low profitability firms tend to have stronger correlation with the aggregate risk premium as proxied by the dividend yield during expansions. During recessions, this phenomenon is also observed through the point estimates, but again none of them are statistically significant. In addition, there is evidence of asymmetry across the two states for low profitability versus high profitability portfolios. The low profitability portfolio's sensitivity to dividend yield increase from -0.05 to 0.31 as the economy changes from recession to expansion, while the high profitability portfolio's sensitivity to dividend yield actually decreases from 0.24 to 0.17.

I perform a simple stylized trading exercise to determine the economic value of the switching model. The results are presented in Table 1.5.5; lowest and highest profitability portfolios represent decile 1 and 10 of the profitability portfolios. The conditional return for time t is recursively calculated using only information prior to time t. The switching portfolio consist of positions in which if the conditional return is positive, I go long in the portfolio. Otherwise, I will invest in one-month T-Bill. The table shows the annualized return and volatility in percentage, as well as the Sharpe ratio. In the full sample, the switching portfolio generates higher return and lower volatility for the low profit firms. This leads to a considerably higher Sharpe ratio of 0.48 compared to 0.048 for the buy-and-hold portfolio. For the high profit firms, switching portfolio results in lower average return. However since the volatility of the switching portfolio is lower than the buy-and-hold, the Sharpe ratio ends up being higher. During recessions, the buy-and-hold portfolio for low profit firms has negative return of -21.54 percent while the buy-and-hold portfolio for high profit firms has negative return of -0.87 percentage. The switching portfolio increases the negative return to -4.11 percent for the low profit firms while simultaneously decreasing the volatility. For the high profit firms, the switching portfolio increases the average return to a positive 4.95 percent while again decreasing the volatility. The pattern during expansions is similar in which the switching portfolio always decreases the volatility and increases the average return of the low profit portfolio. For the high profit portfolio, switching results in a lower average return but it compensates by reducing the volatility by a significant amount, so that the risk-and-return profile improves in the form of a higher Sharpe ratio.

Given the model of expected return, I can discuss the conditional profitability premium and its relationship with the business cycle. Figure 1.5.4 displays the expected profitability premium implied by the model from 1963 to 2013, using the parameter estimates from Table 1.5.4. The premium is defined as the difference between conditional excess return of the high profitability portfolio minus the conditional excess return of the low profitability portfolio. As before, the NBER recessions are shaded.

The conditional premium is mostly positive. It tends to increase prior to and during the early stage of recessions, and decrease afterwards. The qualitative inference is that the expected profitability premium is cyclical: it increases during recessions. This is consistent with the results based on linear regression. As the economy plunge deeper into recessions, the unprofitable firms are struck harder.

Variations in expected returns by themselves do not lead to a full understanding of the risk associated with the portfolios. Investors care about both return and the volatilities associated with the return. A popular measure that summarize the premium per unit of risk is the Sharpe Ratio. Previous papers on expected Sharpe Ratio using U.S. data such as Kandel and Stambaugh (1990) and Tang and Whitelaw (2011) find that it is strongly cyclical. Figure 1.5.5 shows the conditional Sharpe Ratio of high profitability and the low profitability portfolios with NBER recessions shaded.

The ratios for profitable and unprofitable firms are very similar, and they are both strongly cyclical, in line with the previous findings. The ratio increases rapidly in the final stage of the recession and then quickly drops off. Finally, the Sharpe Ratio for the high profitability portfolio is almost always higher than that of the low profitability portfolio. Thus both the cyclicality of the profitability premium and the unconditional premium are not consistent with a systematic risk explanation. The low profitability portfolio seems to have higher volatilty, lower return, lower premium per unit of risk, and they tend to underperform during bad times when the investors care the most about their wealth.

So far, I have investigated a set of relevant payoff characteristics that are usually associated with risk premium. Based on these characteristics, there is no evidence suggesting that profitable firms are fundamentally riskier. An alternative explanation for the premium is that the profitable firms are mispriced relative to the unprofitable firms due to some systematic bias on the part of the market participants. The next section examines this possibility.

1.4. Is there Mispricing?

Abundant evidence in psychology indicates that individuals can form their expectation of the future based on simple heuristics that do not take into full account the underlying process. These naive expectations can lead to distortions in stock prices in a predictable way. Academics have long argued that the predictive power of many financial ratios such as book-to-market is due to the fact that they capture systematic errors in the way investors form expectations about future return. Based on this framework, one possible reason for the low return of unprofitable firms is that the investors are overoptimistic about their future performances relative to the profitable firms. These firms might be currently capturing the attention of market participants because they are new companies in "hot" sectors. While they have very low cash flows currently, investors are willing to hold them due to naive expectations about their future growth that is too extreme, and therefore fail to materialize.

This story is similar to the growth and glamour story advocated by LSV in explaining the value/growth effect. While the mechanism is the same, the story plays out quite differently. The glamour story argues that naive investors become overoptimistic about the stocks that are in-favor due to a series of good news or good past performance. They naively extrapolate the performance of these firms, and if arbitrage by rational market participants are incomplete, this leads to overpricing of these firms. Moreover, the sell-side analysts have a tendency to recommend these glamourous stocks (Jegadeesh et al. (2004)), leading to overoptimism in their earnings forecast.

In the case of profitability, the overoptimism does not come from good past performance. Rather the unprofitable firms have worse past return and earnings, and they also tend to be newer firms and are more likely to be in financial distress. Although investors seem to be betting on these poor performers recovering, in general, they do not.

Expectation Error. Table 1.5.6 displays the expectation error across the portfolios. For each firm-year in the sample, I use the last mean analyst forecast given prior to portfolio formation in July. The expectation error is computed as the difference between the mean "street" forecast earning and the actual "street" earning, both reported by IBES. I winsorize the extreme outliers at the 1% level and report the average error in expectation for each portfolio. The errors across all the profitability portfolios turn out to be positive, indicating that on average the analysts tend to give overly optimistic forecast. This is consistent with previous studies such as Dreman and Berry (1995) that show analysts typically produce upwardly biased forecasts. This optimism can result from errors in processing earnings-related information or a rational response to their economic incentives. Easterwood and Nutt (1999) argue that this can also be due to analysts underreacting to negative information and overreacting to positive information.

More interestingly for our study, the first row shows a monotonically decreasing relationship as one moves from the most unprofitable portfolio to the most profitable portfolio. For the firms in the lowest profitability decile, the average expectation error is 0.175. This is more than five times the average expectation error in the highest profitability decile. Analysts' forecasts for low profitability firms are biased much more in the positive direction than for unprofitable firms.

Panel A of Table 1.5.6 also shows the expectation errors across different states of the economy. If the premium is indeed partly driven by the overoptimism of the investors, then how the overoptimism changes might yield some insight into the cyclical behavior of the premium. Specifically I consider states of the economy as given by recessions and expansions, as well as times of high sentiment and times of low sentiment. The recession and expansion periods are taken from NBER. Baker and Wurgler (2006) have argued that investor sentiments have an effect on the cross-section of stock returns. I use the sentiment index that they constructed, and define periods of high sentiment as those in which the sentiment index is above the 75 percentile, and periods of low sentiment to be times when the sentiment index is below the 25 percentile. The results show that analysts' positive bias increases during times of recession and times of high sentiment. Hribar and McInnis (2012) provide evidence that high sentiment leads to more optimistic forecast for "uncertain" and "difficult-to-value" firms. In this case, these firms are also exactly the unprofitable firms. During times of high sentiment, the upward bias increases more for the firms with low profitability. This might lead to further overpricing of these firms, and thus lower subsequent returns.

Panel B of the table displays the long term growth forecast of earnings given by the analysts, and the dispersion of growth forecast, earnings forecast, and forecast error as given by the standard deviation. I use the last growth forecast given by the analyst prior to portfolio formation. The lowest profitability decile has the highest average growth forecast of 25%. This suggests that the analysts are unconditionally most optimistic about these unprofitable firms. The dispersion of growth forecast, earnings forecast, and forecast errors are meant to capture the uncertainty regarding the performance of the firms. The results indicate that dispersions of all the three variables tend to be higher for the unprofitable firms. These unprofitable firms tend to be worse performing and therefore have higher uncertainty about their future prospects. Diether et al. (2002) provide evidence that stocks with higher dispersion in analysts' earnings forecast earn lower subsequent returns. While their results are consistent with mine, their explanation cannot be the driving force behind the profitability premium. They argue that when there is more uncertainty surrounding a stock, the prices will reflect the view of the more optimistic investors as those with the lowest valuation face a short-sell constraint. They are directly relating the uncertainty to future stock return, but this fails to address why there should be higher systematic overoptimism for the firms with more dispersion *as given by analysts*. These analysts are not subject to any buying or selling constraints imposed by the structure of the market as they are only providing their estimate of the firm's performance.

Table 1.5.7 investigates the expectation error hypothesis further by dividing the returns into announcement period returns and non-announcement period returns. Announcement period is defined as the three-day window consisting of the day before, the day of, and the day after the earnings announcement. If the low returns of the lowest profitability decile are truly driven by expectation error, most of the negative returns should be concentrated around the earnings announcement, when the overoptimism of the investors is revealed. This is indeed what the table shows. The last row reports the proportion of returns that can be attributed to the announcement and non-announcement periods. For the least profitable portfolio, the overall return is negative, and over 70% of that negative return takes place in the three-day announcement window. The rest of the portfolios does not show a clear pattern.

Ball et al. (2015) show that profitability can predict returns up to five years into the future. From that, they argue that the driver of the premium must be risk-based. Mispricings tend to be corrected once market participants discover them and these opportunities cannot last for extended period of time. Therefore, the fact that profitability has persistent power in predicting future returns is an indication that it is a true risk premium. This argument, however, is predicated on the fact that market participants understand the mapping between profitability and subsequent return. The new measures of profitability that have been the interest of recent papers are different from the return on equity that investors used to focus on. It is very possible that market participants have not been paying attention to these ratios prior to the study. This, along, with the high persistence of the profitability measure itself, can contribute to its ability to forecast returns up to several years into the future.

Figure 2 shows the persistence of profitability. I examine the firms that were in each of the profitability deciles five years prior, as shown in the horizontal axis. For the firms in each decile, I plot the average decile portfolio that they are in in the current year. The figure shows that out of the firms in decile 1 of profitability five years before, the average profitability decile is approximately 3.8. Out of the firms in the highest decile of profitability, their average current decile is 8. There is a monotonically increasing relationship between profitability deciles five years prior and today. Thus profitability itself tends to persist into the future. A firm that is profitable this year will tend to remain profitable five years from now.

In order for the mispricing story to be consistent with persistent forecasting power of profitability, the market participants should not completely understand the mapping between profitability and future performance. If they do, then even if profitability itself is persistent, they learn after the observing their mistakes in the first year and correct their expectation for subsequent years. Figure 3 explores whether investors learn from their past errors. The horizontal axis displays the portfolio deciles, while the vertical axis shows the average analyst forecast errors. I investigate the expectation error for portfolio formed from year $t-1$ to year $t-5$.

Surprisingly, the results show that the expectation error can persist for up to five years into the future. The blue line shows the expectation error for the portfolio formed just one year prior. This result resembles those shown in Table 1.5.6, and a clear monotonically decreasing trend appears in forecast error as the profitability decile increases. For the portfolios formed from $t-2$ to $t-5$, the monotonically decreasing relationship persists. The only exception is the lowest profitability decile 1. This is because the firms that miss their forecast by the most tend to drop out of the sample, so the ones that are still in the sample tend to have done better and mechanically less forecast error. From decile 2 to decile 10, the analyst forecast error decreases, even for the portfolios that are formed five years before. The investors' errorenous perception of the mapping between profitability and expectation errors actually persist. This evidence casts some doubt on the notion that investors actually understand the mapping between profitability and performance. In fact, it seems that they are not paying attention to this measure, and the expectation errors can last years into the future.

What Drives the Expectation Error? Given the wedge between forecasted and actual performance, there is a misunderstanding of the mapping from profitability to future stock return. This might be due to investors previously not focusing on the new measure of economic profit that is the subject of recent research. But why is the bias systematically decreasing in the profitability? There are two possible reasons for what leads to the over-optimism of investors. The first possibility, suggested by LSV, is that investors naively extrapolate the past good performance of firms too far into the future. They believe that firms should continue to do well in the future and therefore over-estimate the earnings. If this hypothesis is true, then unprofitable firms should have better prior performance, perhaps using a different measure of performance than profitability, than do profitable firms. Alternatively, the investors' over-optimism might result from failing to anticipate how persistent the bad performance of unprofitable firms can be. This hypothesis would suggest that unprofitable firms have done poorly prior to portfolio formation, and they continue to do poorly just after portfolio formation. Investors naively believe that these underperforming firms will mean-revert and recover, but their expectations fail to materialize. This section tries to distinguish between the two possibilities.

I begin by examining some firm characteristics across the profitability portfolios as shown in Panel A of Table 1.5.8. Consistent with prior work, high profitability firms tend to be larger in size and they tend to have low book-to-market. This negative correlation means that profitability can be used as a hedge for value strategies and they work especially well jointly. The lowest profitability decile portfolio has the smallest median firm age of 5.6, suggesting that they tend to be younger firms. The highest profitability decile portfolio has a median age of 7.3 while across the portfolios, the highest median age is 11. So while the youngest firms are not profitable, the most mature firms are not profitable either because they are already past their fastest-growing phase. The most profitable firms tend to be somewhere in between.

Unprofitable firms tend to have the highest net stock issuance. This is mostly concentrated in the lowest profitability decile, with an average net issuance more than twice that of any other portfolios. Previous studies such as Pontiff and Woodgate (2008) have shown that firms tend to underperformance after seasoned equity offerings. This negative performance is often attributed to market timing by the corporate insiders. When they feel that the stock is overpriced, they issue shares to cash in on the over-valuation. In the case of the profitability premium, this explanation is difficult to reconcile with the fact that the unprofitable firms have been performing badly over the past few years. Indeed, Loughran and Ritter (1995) showed that firms tend to issue new equities following a run-up in their prices. The high net issuance of the unprofitable firms might instead be because these are young firms that need capital. The earnings yield and asset growth also point in the same direction. Unprofitable firms have negative earnings on average, again mostly concentrated in the lowest profitability decile. The earnings yield does not exhibit a strong pattern across the other profitability portfolios. The most unprofitable firms also have negative asset growth and the asset growth increases across the profitability portfolios. Both suggest that these are not the glamorous firms that have been quickly growing or expanding. Instead, they seem to be struggling and shedding assets.

One of the anomalies that the profitability factor is able to explain is the return premium associated with financial distress. Firms in higher distress (higher probability of bankruptcy) tend to earn lower returns. Panel B of Table 1.5.8 studies several measures of distress across the profitability portfolios. EDF is the Expected Default Frequency given by the Merton (1974) model that computes default probability for individual firms at the monthly frequency. The model recognizes the equity of the firm as a call option on the firm's unobserved underlying value with a strike price equal to the book value of the firm's debt. It then proceeds to apply classic option pricing theory to obtain the firm value and volatility. The firm's probability of default is backed out as the probability that the firm's value will drop below the face value of its debt. This model has appeared widely in academic papers such as Vassalou and Xing (2004) and Bharath and Shumway (2008). The details of the derivation and implementation of the iterative process can be found in Bharath and Shumway (2008). I also examine accounting based measures of distress as given by the Ohlson (1980) O-score, label "Ohlson O-Probability" is 0.43 percent. This probability is calculated via a logistic transformation of the Ohlson O-score[2]. Finally I obtain credit rating and default data from Moody's Default and Recovery Database (DRD) and match it to the firms in the sample.

More profitable firms have lower distress risk than less profitable firms by all of these measures. Moreover, most of the differences are driven by the high distress of low profitability portfolio. The O-Probability ranges from 0.06 percent to 0.15 percent for Portfolios 2 to 10, but jumps more than ten times to 1.69 for the least profitable Portfolio 1. The EDF for portfolios 1 to

[2]The O-score is defined as

$$\begin{aligned} O-score &= -1.32-0.407log(total\ assets)+6.03\left(\frac{total\ liabilities}{total\ assets}\right)-1.43\left(\frac{working\ capital}{total\ assets}\right) \\ &+0.076\left(\frac{current\ liabilities}{current\ assets}\right)-1.72\boldsymbol{I}(total\ liabilities>total\ assets)-2.37\left(\frac{net\ income}{total\ assets}\right) \\ &-1.83\left(\frac{funds\ from\ operation}{total\ liabilities}\right)+0.285\boldsymbol{I}(net\ loss\ for\ last\ two\ years) \\ &-0.521\left(\frac{net\ income_t-net\ income_{t-1}}{|net\ income_t|+|net\ income_{t-1}|}\right) \end{aligned}$$

where $\boldsymbol{I}(\cdot)$ is an indicator function that equals 1 if the condition is satisfied and 0 otherwise.

10 are monotonically decreasing with the difference between decile 1 and decile 2 significantly larger than the difference between any two consecutive portfolios. The proportion of default for the lowest decile is 0.44% and it decreases to merely 0.03% for the highest decile. The overall conclusion is that the unprofitable firms tend to be performing poorly based on other metrics and they experience higher financial distress, with the distress risk mostly concentrated in the lowest decile of profitability.

Table 1.5.9 shows the past and future stocks returns as well as sales and earnings growth across the profitability portfolios. The average past year return of firms in the lowest profitability decile is 5.5% while the average return for the firms in the highest profitability decile is 25.2%. There is a monotonically increasing relationship between profitability and past 1 year return. The same relationship holds for the past 5-year cumulative returns in the next row. Contrary to the glamour story, it is in fact the profitable firms that have done well in the past. Over the year subsequent to portfolio formation, the previously profitable firms continue to perform well, while the previously unprofitable firms continue to underperform. Over the next five years, however, the returns equalizes somewhat and the clear monotonic relationship disappears, even though the cumulative return for the least profitable portfolio still lags behind that of the other portfolios. It is almost as if the investors expect the performance to mean-revert with the high profitability firms underperforming while the low profitability firms outperforming but the mean-reversion does not happen as quickly as the investors think. It takes more than five years for the reversion in stock return to materialize, and over the next year the profitable firms continue their trend of outperformance.

The table also examines accounting measures of performance, as given by the sales and earnings per share (EPS) growth. I compute the annualized growth rates by fitting a least squares growth line to the logarithms of the six annual observations. Thus the growth rate for year t is computed as the least squares growth line from year $t-5$ through year t. This follows the same construction procedure used by IBES and Dechow and Sloan (1997). I only keep the variable if there are at least 5 years of data available.

The pattern of short term trend and long term reversal is more pronounced through sales and EPS growth. Over the past five years, the low profit firms have slower sales growth than the high profit firms. Over the next five years, however, the sales growth becomes similar across the portfolios, suggesting that the sales mean-revert over the subsequent five year period. The EPS growth for the lowest profitability decile is -0.0184 as compared to 0.0244 for the highest profitability decile. Again, unprofitable firms have lower earnings growth so they are not really the glamour firms in the sense of having superior past performances. Interestingly over the next five years, the EPS growth pattern reverses itself. The lowest profitability decile has a growth rate of 0.0306 while the highest profitability decile has a negative growth rate of -0.0105. Mean-reversion in performance does occur, but it happens over the next five years.

Finally, I carry out a portfolio double sort to further understand the relationship between expectation and profitability. The main proxy of expectation that I use is the median growth forecast of the companies issued by the analysts. A higher forecasted growth rate indicates a more positive expectation for the performance of the firm. The goal of the exercise is to investigate whether the difference in expectation captured by profitability is reflected in stock returns, and if so, what that would reveal about the the reason behind the expectation error.

Table 1.5.10 displays the results with value-weighted returns. The spread in the profitability premium is mainly concentrated among the firms with the highest forecast of growth. The average monthly percentage return differential between the high profit and low profit firms in quintile 1 of forecasted growth is 0.29, and the differentials become -0.2 and 0 in quintile 2 and 3. For quintile 4 the differential is slightly higher at 0.13. The return differential is 1.11 in the highest estimated growth quintile, more than three times higher than any of the other return differentials. The striking result is that the lowest portfolio return by far is the low-profitability, high expectation portfolio (0.19%). This is consistent with the expectation error hypothesis. Those with the high forecast growth are the same firms that investors are most optimistic about, and the low profitability firms are the firms that are more likely to perform poorly. Thus one would expect these firms to miss their forecast by the most, and therefore displays the lowest return.

The table also displays the average forecast error, forecast growth, and profitability of each of the 25 portfolios. These numbers provide additional insight regarding exactly what the investors are wrong about. First I examine profitability across the portfolios. For profitability quintiles 2 to 5, there is virtually no difference across the forecast growth. The profitability of the firms with the lowest growth forecast is roughly the same as the profitability of the firm with the highest growth forecast. However, quintile 1 displays something more interesting. The profitability of those with the highest growth forecast is much lower than the rest. This means that among these unprofitable firms, the analysts are expecting the highest growth for the firms that are extremely unprofitable. They are expecting the performance of these firms to mean-revert back up. Yet these firms do not as they again tend to miss their earning forecast on the low side. This contributes to the extreme small return observed for this portfolio. An alternative way to look at this is through the growth forecast of each of the portfolios. The highest growth forecast is given by the portfolio in quintile 5 of growth forecast and quintile 1 of profitability. Thus, among those companies with high forecast growth, analysts feel most optimistic about the extremely unprofitable firms as they expect poor performers to recover.

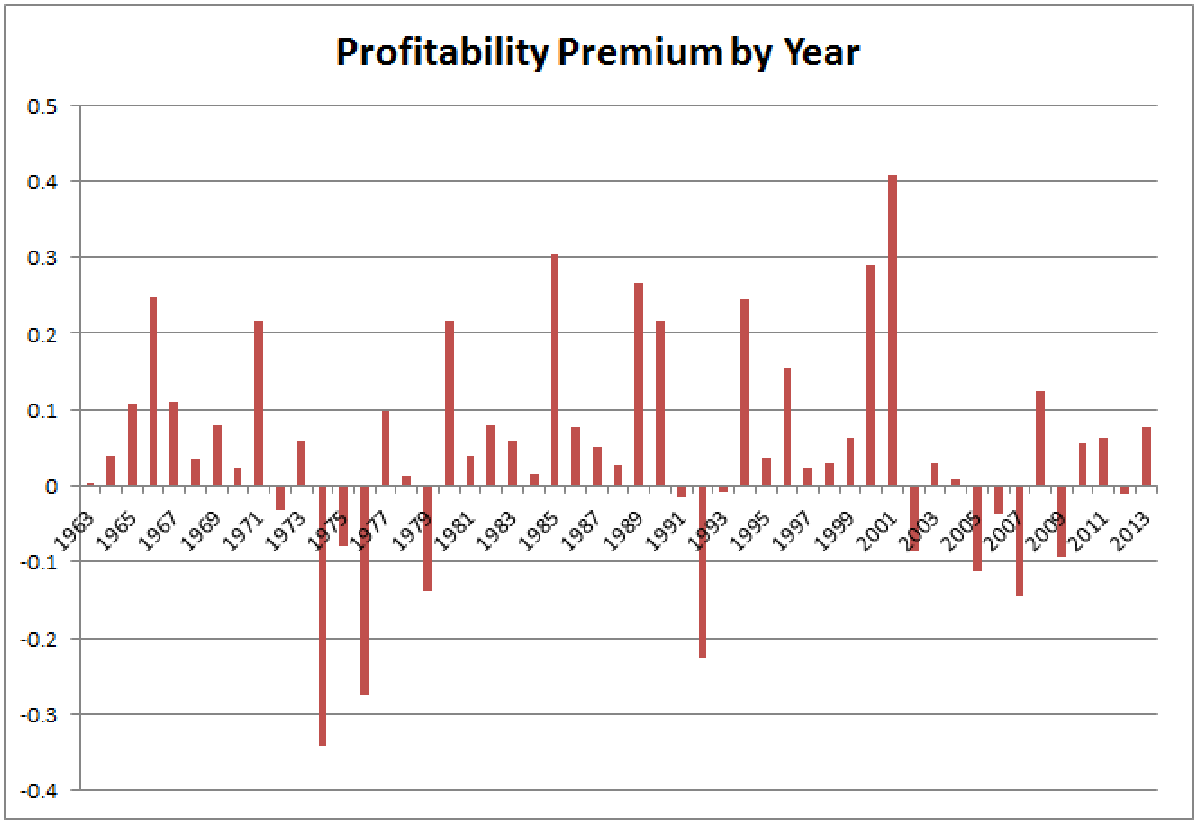
1.5. Conclusion

Profitability has been shown to be a significant and robust determinant of the cross-section of stock returns. It works exceptionally well in combination with book-to-market in generating high spreads in return premium. More importantly, it has been shown to be able to explain most of the existing asset pricing anomalies. Profitability's importance has led to its incorporation into a new benchmark factor model. Given its exceptional empirical performance, the natural next step is to investigate whether the economic mechanism behind its power is based on systematic risk or behavioral mispricing.

This paper finds that the time series pattern of the premium is incompatible with systematic risk. The profitability premium is quite consistent through time. Profitable firms have higher returns and less volatility than unprofitable firms, leading to a significantly higher Sharpe ratio. Profitable firms also have lower drawdown. More fundamentally, the premium is shown to be countercyclical, with the premium increasing during bad times. Thus unprofit firms perform even worse than profitable firms during recessions when the marginal utility of wealth is high. Unprofitable firms do not provide a hedge for bad times.

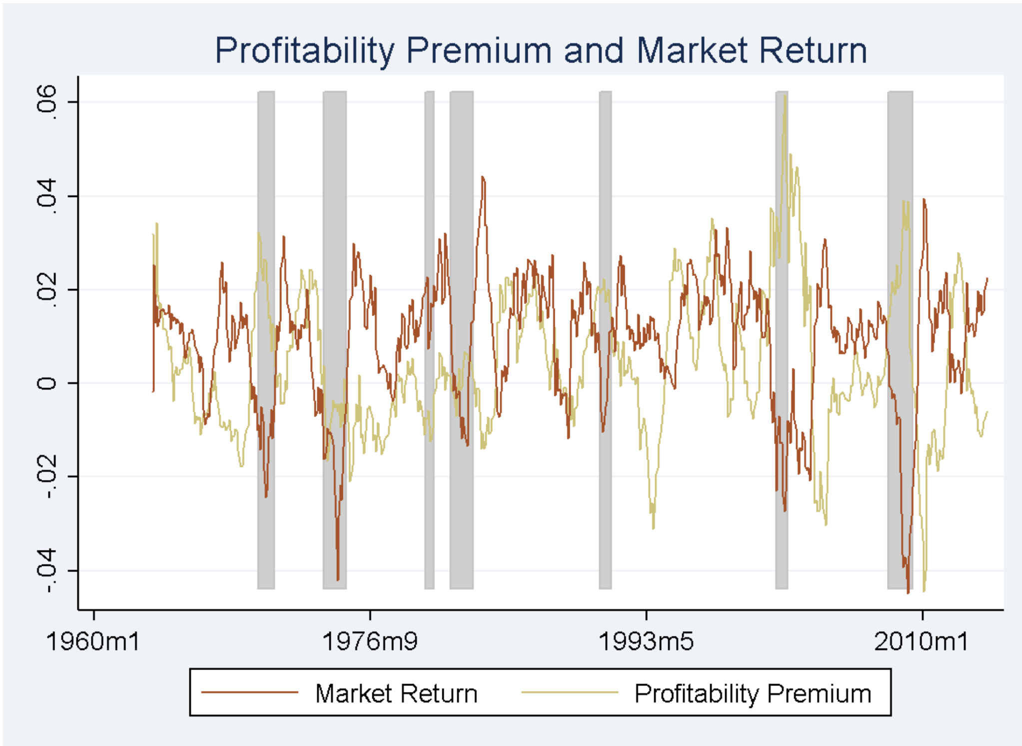
I investigate the channels for mispricing and show that the analysts tend to be much more optimistic and overestimate the earnings of the firms that are unprofitable relative to the profitable firms. This forecast error is surprisingly persistent. Porfolios that are formed based on profitability deciles five year prior still display this monotonic relationship in forecast errors. I argue that the forecast error is not due to the glamour effect, in which market participants extrapolate the future performance of the firms based on past performance. Indeed the unprofitable firms are not the firms that have performed well in the past. Rather, they tend to be younger firms without consistently positive cash flow, and have higher probability of being in financial distress. While one cannot conclusively reject the possibility that profitability is related to systematic risk, any risk-based theoretical model that attempts to explain it in the future must take into consideration its correlational structure with the macro business cycle.

Figure 1.5.1. Profitability Premium 1963 to 2013



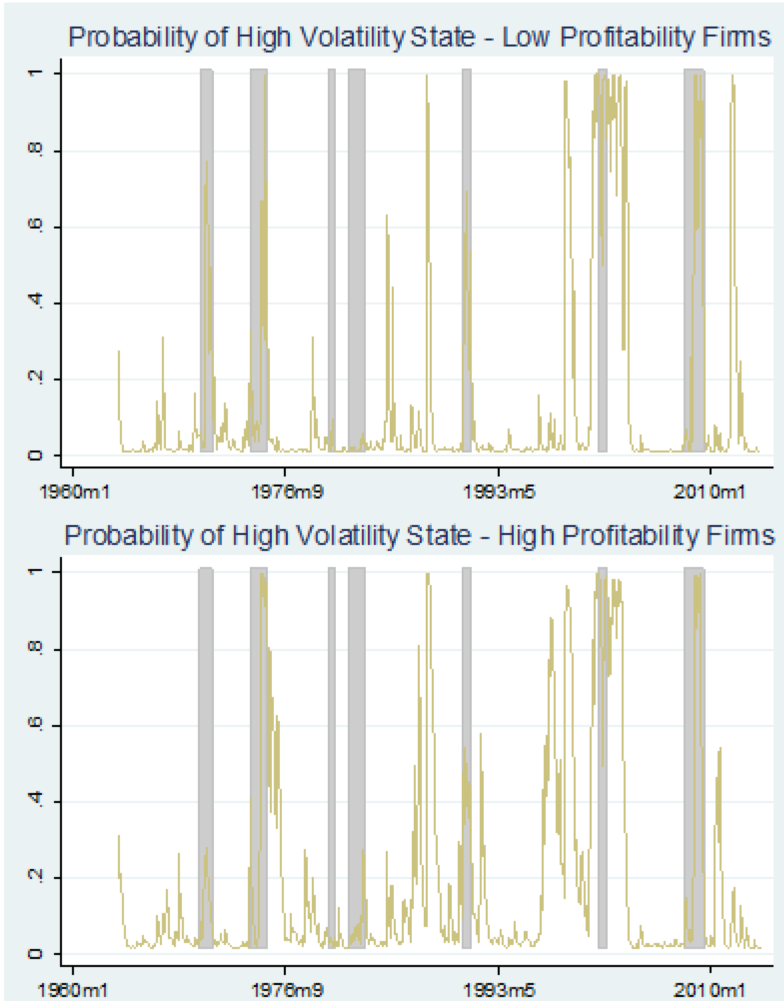
All the companies in the sample are sorted into ten portfolios based on their operating profitability, excluding the financial firms (those with one-digit standard industrial classification code of six). The profitability premium is calculated as the annual return of highest decile profitability portfolio minus the lowest decile profitability portfolio. The sample period is from July 1963 to December 2013, so the first and last year only include six months of return.

Figure 1.5.2. Profitability Premium and Market Return



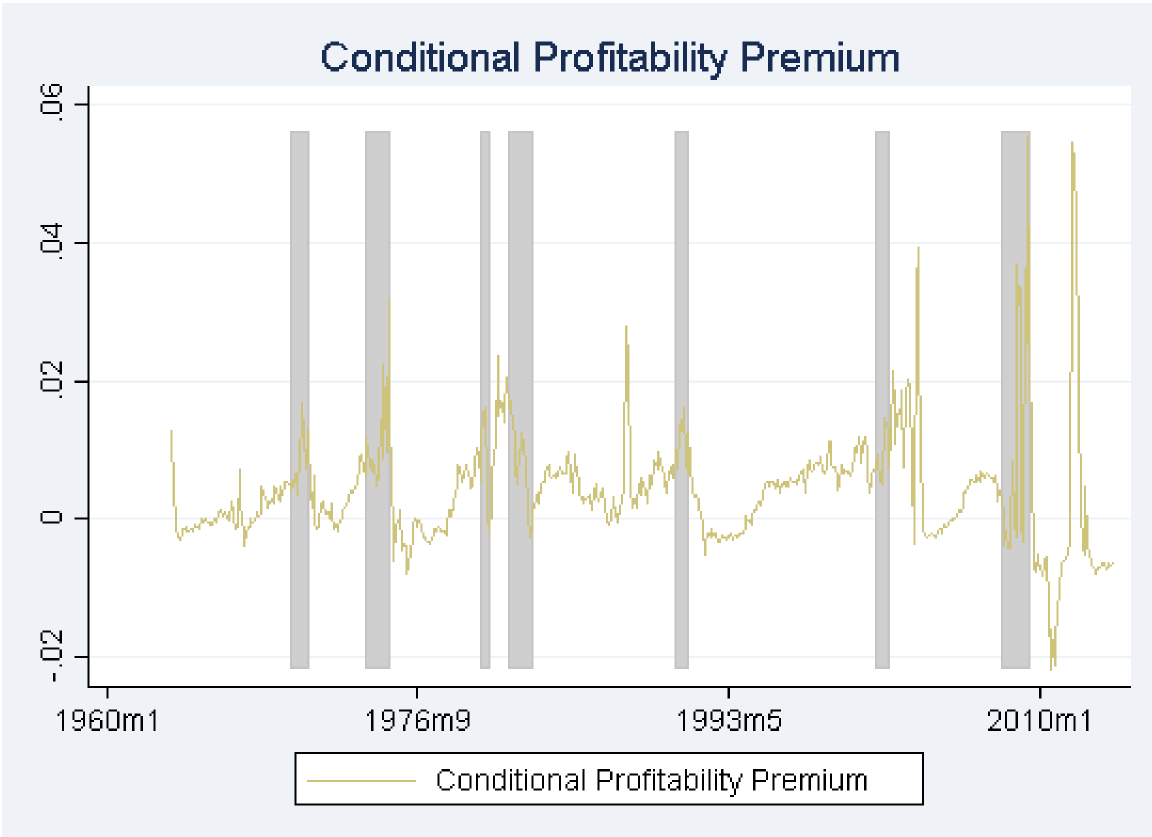
This figure plots the return of highest decile profitability portfolio minus the lowest profitability portfolio. The premium is smoothed over 12 months. For comparison, the figure also plots the 12-month smoothed aggregate market return as given by the CRSP value-weighted index. The NBER recessions are shaded. The sample period is from July 1963 to December 2013.

Figure 1.5.3. Probability of High Variance States



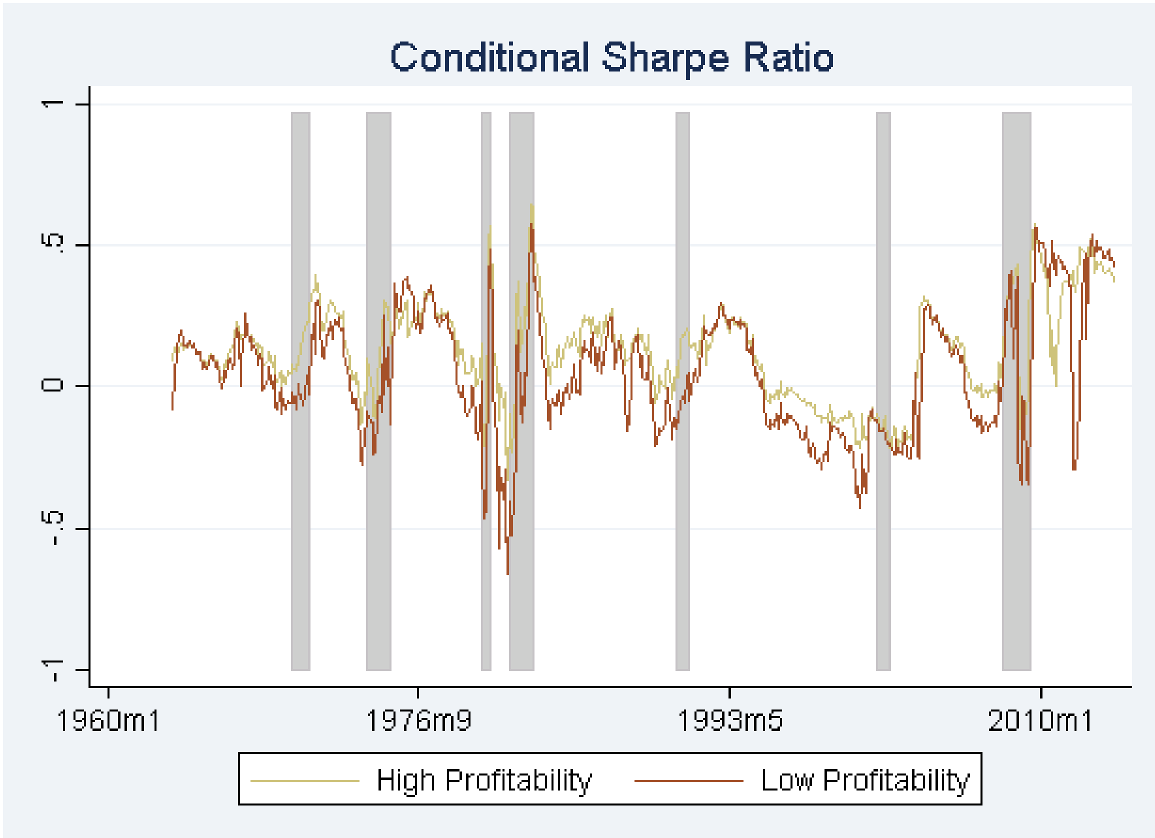
This figure plots the probability of being in a high volatility state as given by the two-state Markov Regime-Switching model. The top plot shows the probability given by the model fitted to the high profitability portfolio and the bottom plot shows the probability given by the model fitted to the low profitability portfolio. The NBER recessions are shaded. The sample period is from July 1963 to December 2013.

Figure 1.5.4. Conditional Profitability Premium



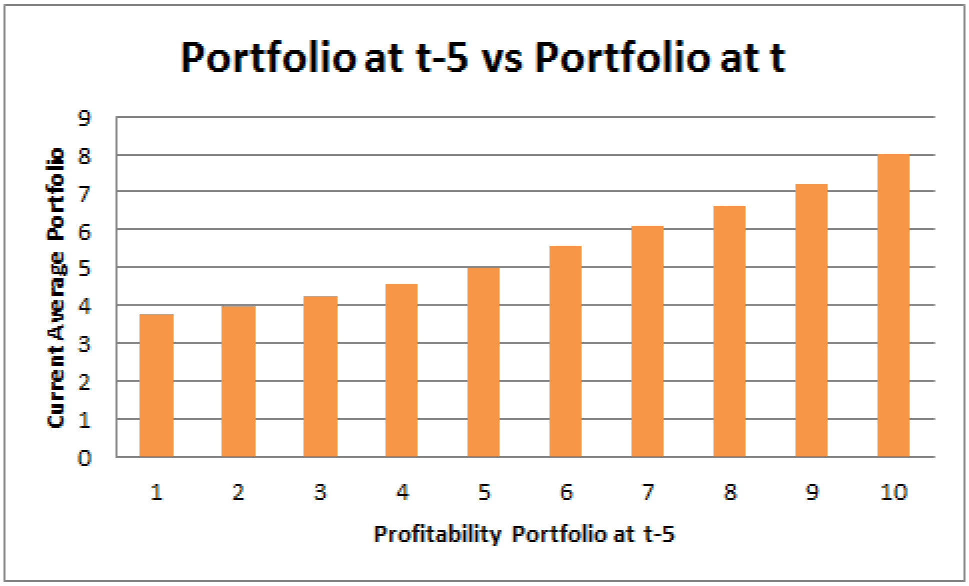
This figure plots the expected profitability premium at time t conditional on information at time t-1, as given by the two-state Markov Regime-Switching model. The premium is calculated as the expected excess return of the top profitability decile minus the expected excess return of the bottom profitability decile. The NBER recessions are shaded. The sample period is from July 1963 to December 2013.

FIGURE 1.5.5. Expected Sharpe Ratio



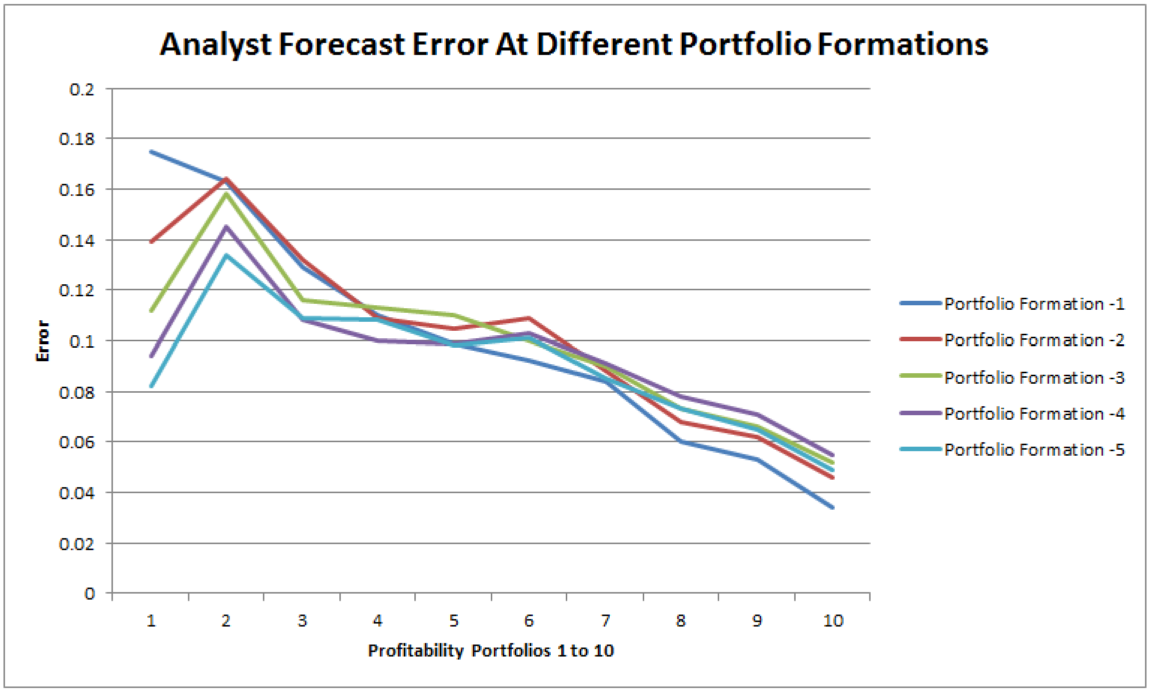
This figure plots the expected Sharpe Ratio at time t conditional on information at time t-1, as given by the two-state Markov Regime-Switching model. The ratio is calculated as the expected excess return fitted by the model divided by the expected volatility fitted by the model. The yellow line shows the conditional Sharpe ratio for the high profitability portfolio while the red line shows the conditional Sharpe Ratio for the low profitability portfolio. The NBER recessions are shaded. The sample period is from July 1963 to December 2013.

FIGURE 1.5.6. Profitability Persistence



This figure shows the persistence of profitability portfolios. The horizontal axis displays the ten decile portfolios of profitability from year t-5. For the firms in each decile from five years ago, the vertical axis displays the average portfolio the firms are in at time t. The sample period is from July 1963 to December 2013.

FIGURE 1.5.7. Expectation Error from t to t-5



This figure shows the persistence of expectation errors. It plots the analyst forecast error in the vertical axis across the ten operating profitability portfolios in the horizontal axis. The error is calculated as difference between the forecast earnings per share and the actual earnings per share reported by IBES, winsorized at the 1% level. The portfolio formation range from year t-1 up to year t-5. The sample period is from July 1975 to December 2013.

Table 1.5.1. Risk Across Portfolios

This table reports various measures of risk being applied to the ten operating profitability portfolios. Panel A displays the average holding period returns for 1 month, 1 year, 3 year and 5 years. It also shows the volatility and Sharpe ratio of the portfolios, as well as the worse drawdown for periods ranging from 3 months to 2 year. Panel B decomposes the beta of the portfolios with respect to the market into two components: one associated with discount rate news and one associated with cash flow news. The sample excludes financial firms (those with one-digit standard industrial classification code of six) and goes from July 1963 to December 2013.

	Profitability Portfolios									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Return-based Measures										
Monthly Return	0.00163	0.004	0.00515	0.00516	0.0059	0.00586	0.00514	0.00671	0.00565	0.00565
1-Year Holding Return	0.075	0.1	0.114	0.113	0.123	0.12	0.113	0.132	0.118	0.118
3-Year Holding Return	0.197	0.304	0.359	0.35	0.391	0.387	0.363	0.426	0.377	0.385
5-Year Holding Return	0.3	0.537	0.66	0.644	0.708	0.732	0.683	0.8	0.693	0.717
Volatility	0.236	0.175	0.167	0.166	0.167	0.162	0.165	0.170	0.162	0.169
Sharpe Ratio	0.084	0.281	0.380	0.385	0.439	0.448	0.386	0.491	0.431	0.413
Worst 3-Month Drawdown	-0.51	-0.33	-0.37	-0.36	-0.39	-0.26	-0.34	-0.37	-0.31	-0.33
Worst 6-Month Drawdown	-0.58	-0.51	-0.43	-0.47	-0.48	-0.35	-0.44	-0.41	-0.34	-0.34
Worst 1 Year Drawdown	-0.74	-0.54	-0.44	-0.49	-0.49	-0.4	-0.44	-0.44	-0.42	-0.45
Worst 2 Year Drawdown	-0.86	-0.6	-0.49	-0.46	-0.5	-0.42	-0.45	-0.41	-0.45	-0.5
Panel B: Beta Decomposition										
Discount Rate Beta	0.676	0.526	0.522	0.529	0.482	0.483	0.543	0.571	0.571	0.585
Cash Flow Beta	0.792	0.584	0.521	0.556	0.552	0.519	0.522	0.556	0.498	0.499

Table 1.5.2. Summary Statistics for Value, Size and Profitability Premium

This table reports descriptive statistics of value-weighted portfolios based on size, book to market, and operating profitability. For each variable, the firms are sorted into ten deciles based NYSE breakpoints. The premium is calculated as the difference between the top decile and the bottom decile. The market return is given by the value-weighted CRSP index. Recession periods are defined by the NBER. The sample excludes financial firms (those with one-digit standard industrial classification code of six). The sampling period is from July 1963 to December 2013

	Premium	Recession Premium	Expansion Premium	Correlation with Market Return
Value Premium	0.67	0.76	0.66	-0.0493
Size Premium	0.37	1.03	0.27	0.321
Profitability Premium	0.40	0.69	0.36	-0.334

Table 1.5.3. Long Horizon Regression of Profitability Portfolios on Aggregate Variables

This table reports long horizon regression results for each of the ten profitability deciles. The independent variables include one-month U.S. treasury rate, the aggregate default spread as given by the yield difference between Moody's Aaa and Baa bonds, and the aggregate dividend yield. Regression results are reported for one-month, two-month, six-month, and twelve-month cumulative returns. The Newey-West standard errors correcting for overlapping returns are reported in parentheses. The sample excludes financial firms (those with one-digit standard industrial classification code of six). The sampling period is from July 1963 to December 2013

	Profitability Deciles									
	Low Profitability	2	3	4	5	6	7	8	9	High Profitability
1-Month Return										
Treasury 1 Month	-6.032***	-2.249*	-2.890**	-2.843**	-3.046**	-2.705**	-2.668**	-3.128***	-3.083***	-2.988**
	(1.858)	(1.354)	(1.169)	(1.271)	(1.338)	(1.197)	(1.164)	(1.201)	(1.154)	(1.194)
Default Spread	0.665	0.217	0.756	0.512	0.506	0.495	0.379	0.634	0.423	0.313
	(0.913)	(0.743)	(0.577)	(0.631)	(0.604)	(0.558)	(0.582)	(0.540)	(0.521)	(0.499)
Div Yield	0.486***	0.203**	0.233***	0.245**	0.231**	0.231**	0.284***	0.223**	0.231**	0.227**
	(0.159)	(0.1000)	(0.0897)	(0.0981)	(0.113)	(0.103)	(0.0997)	(0.104)	(0.0935)	(0.113)
2-Month Return										
Treasury 1 Month	-11.89***	-4.197*	-5.407***	-5.144**	-5.746***	-4.553**	-4.832**	-5.683***	-5.605***	-5.376***
	(3.248)	(2.351)	(1.934)	(2.249)	(2.204)	(1.980)	(1.988)	(1.931)	(1.804)	(1.846)
Default Spread	1.389	0.438	1.446	0.988	1.035	0.992	0.735	1.155	0.675	0.514
	(1.703)	(1.442)	(1.080)	(1.254)	(1.154)	(1.057)	(1.106)	(0.983)	(0.987)	(0.914)
Div Yield	0.979***	0.402**	0.461***	0.482***	0.449**	0.423**	0.547***	0.437***	0.454***	0.445***
	(0.264)	(0.165)	(0.154)	(0.166)	(0.177)	(0.164)	(0.163)	(0.158)	(0.143)	(0.170)
6-Month Return										
Treasury 1 Month	-32.38***	-10.56*	-13.00***	-12.32**	-14.79***	-9.961**	-11.72**	-13.81***	-13.25***	-11.59**
	(8.041)	(5.392)	(4.806)	(5.321)	(4.850)	(4.720)	(4.955)	(4.855)	(4.872)	(5.367)
Default Spread	6.056*	3.494	5.155**	4.389*	4.761**	4.576**	3.515	4.682**	2.849	2.500
	(3.621)	(2.673)	(2.375)	(2.453)	(2.381)	(2.217)	(2.219)	(2.282)	(2.212)	(2.274)
Div Yield	2.683***	0.989**	1.229***	1.263***	1.175***	1.034***	1.473***	1.135***	1.198***	1.100**
	(0.759)	(0.494)	(0.397)	(0.399)	(0.382)	(0.371)	(0.410)	(0.394)	(0.391)	(0.505)
12-Month Return										
Treasury 1 Month	-54.47***	-19.43*	-22.71***	-19.33*	-25.70***	-15.01	-17.99*	-21.17**	-18.87*	-15.46
	(14.86)	(10.02)	(8.640)	(10.01)	(8.676)	(9.394)	(10.05)	(9.794)	(10.61)	(11.09)
Default Spread	9.402*	5.500	8.248**	5.976*	9.238***	7.784**	4.705	7.103**	2.773	2.203
	(5.078)	(3.735)	(3.456)	(3.495)	(3.429)	(3.285)	(3.290)	(3.552)	(3.350)	(3.686)
Div Yield	4.670***	1.908*	2.382***	2.436***	2.202***	1.937***	2.882***	2.057***	2.164***	1.881*
	(1.524)	(1.096)	(0.704)	(0.707)	(0.732)	(0.667)	(0.789)	(0.730)	(0.735)	(1.061)

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5.4. Coefficient Estimates in the Markov Regime Switching Model

This table reports coefficient estimates for the two-state Markov Regime Switching model for each of the ten profitability deciles. The dependent variables are the portfolio excess returns. The independent variables include one-month U.S. treasury rate, the aggregate default spread as given by the yield difference between Moody's Aaa and Baa bonds, and the aggregate dividend yield. Standard errors are reported in parentheses. The sample excludes financial firms (those with one-digit standard industrial classification code of six). The sampling period is from July 1963 to December 2013

	Profitability Decile									
	Low	2	3	4	5	6	7	8	9	High
Mean Parameters										
Constant, State 1	-0.064**	-0.0089	-0.032*	-0.05**	-0.01	-0.045	-0.043**	-0.034*	-0.04*	-0.036
	(0.025)	(0.024)	(0.019)	(0.023)	(0.017)	(0.023)	(0.021)	(0.02)	(0.021)	(0.022)
Constant, State 2	-0.029	-0.017	-0.06	0.014	-0.09	0.0076	-0.083	-0.041	-0.093	-0.077
	(0.18)	(0.05)	(0.11)	(0.057)	(0.085)	(0.05)	(0.072)	(0.096)	(0.12)	(0.061)
Interest Rate, State 1	-7.2***	-3.09***	-3.9***	-3.7***	-4.05***	-3.8***	-3.62***	-4.11***	-4.05***	-4.16***
	(1.29)	(1.14)	(1.08)	(1.16)	(0.89)	(1.06)	(1.11)	(1.08)	(1.13)	(1.13)
Interest Rate, State 2	7.26	3.02	3.8	3.55	3.94	3.49	-3.56	4	3.99	3.96
	(12.87)	(3.37)	(8.08)	(3.25)	(5.49)	(3.58)	(7.39)	(9.55)	(6.65)	(8.16)
Default Premium, State 1	1.04*	0.55	1.18**	1.08**	1.33***	1.53***	0.98*	1.1**	1.17**	0.99*
	(0.57)	(0.56)	(0.54)	(0.54)	(0.43)	(0.53)	(0.50)	(0.46)	(0.52)	(0.51)
Default Premium, State 2	-0.58	0.041	-0.61	-0.19	-0.24	-0.25	-0.26	-0.49	-0.32	-0.27
	(4.72)	(1.1)	(2.35)	(1.16)	(2.05)	(1.23)	(2.12)	(3.2)	(2.15)	(2.73)
Dividend Yield, State 1	0.31**	0.081	0.16*	0.22**	0.081	0.19**	0.2**	0.17*	0.19**	0.17*
	(0.11)	(0.098)	(0.084)	(0.094)	(0.071)	(0.096)	(0.088)	(0.088)	(0.088)	(0.092)
Dividend Yield, State 2	-0.05	0.011	0.13	-0.12	0.26	-0.09	0.21	0.052	0.2	0.24
	(0.88)	(0.23)	(0.53)	(0.26)	(0.38)	(0.24)	(0.35)	(0.48)	(0.49)	(0.34)
Variance Parameters										
σ, State 1	0.0022***	0.001***	0.0014***	0.001***	0.0011***	0.0012***	0.0014***	0.0015***	0.0015***	0.0015***
	(0.00016)	(0.0001)	(0.00012)	(0.00012)	(0.00091)	(0.00012)	(0.00013)	(0.00013)	(0.00014)	(0.00012)
σ, State 2	0.021***	0.0051***	0.0062***	0.0051***	0.0072***	0.0046***	0.0058***	0.0073***	0.0057***	0.006***
	(0.0048)	(0.00052)	(0.0011)	(0.00079)	(0.001)	(0.00078)	(0.0011)	(0.0018)	(0.0015)	(0.0013)
Log Likelihood	860.6	1004.42	1021.8	1027.85	1052.98	1031.78	1024.71	1009.73	1021.64	1006.85

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.5.5. Out of Sample Trading Exercise: September 1988 to December 2013

This table reports the results from an out-of-sample trading experiment using the Markov-Regime Switching model. The dependent variables are the portfolio excess returns. The independent variables include one-month U.S. treasury rate, the aggregate default spread as given by the yield difference between Moody's Aaa and Baa bonds, and the aggregate dividend yield. Trading results compares the returns of T-Bill with the lowest and highest decile of portfolios sorted on profitability. The buy-and-hold strategy simply reinvest all the funds in the relevant portfolio. Switching portfolios take a long position if the recursively estimated mean is positive, otherwise it will invest in one-month T-Bill. All variables are annualized.

		Lowest Profitability		Highest Profitability	
	T-Bills	Buy-and-Hold	Switching Portfolio	Buy-and-Hold	Switching Portfolio
Full Sample					
Mean Return	3.27	4.6	9.98	13.44	12
SD of Return	0.66	26.92	13.1	17.15	11.41
Sharpe Ratio		0.048	0.48	0.55	0.72
Recession					
Mean Return	2.8	-21.54	-4.11	-0.87	4.95
SD of Return	0.68	45.04	19.3	24.6	15.79
Sharpe Ratio		-0.59	-0.55	-0.15	0.18
Expansions					
Mean Return	3.37	8.79	12.17	15.56	13.01
SD of Return	0.65	23.24	11.98	15.83	10.68
Sharpe Ratio		0.22	0.98	0.71	1.08

Table 1.5.6. Expectation Errors Across Portfolios

Panel A of this table reports the analyst forecast error across the operating profitability portfolios. The error is calculated as difference between the forecast earnings per share and the actual earnings per share reported by IBES, winsorized at the 1% level. The table also reports the forecast error across recessions and expansions, and for times of low sentiment and times of high sentiment. Sentiment index is taken from Jeffrey Wurgler's website and high sentiment is defined as periods in which the index is above the 75 percentile, and low sentiment is defined as periods in which the index is below the 25 percentile. Panel B of the table reports the growth forecast by the analyst as well as the standard deviation of the growth forecast, earnings forecast and forecast errors. The sample period is from July 1975 to December 2013.

	Profitability Portfolios vs Mis-Expectation									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Expectation Error										
All Periods	0.175	0.161	0.13	0.108	0.101	0.091	0.084	0.06	0.053	0.034
Expansion	0.166	0.153	0.13	0.104	0.1	0.093	0.086	0.061	0.055	0.034
Recession	0.255	0.235	0.133	0.145	0.113	0.08	0.071	0.046	0.038	0.043
Low Sentiment	0.121	0.098	0.053	0.065	0.051	0.037	0.029	0.013	0.018	0.012
High Sentiment	0.206	0.198	0.173	0.134	0.133	0.124	0.118	0.088	0.074	0.046
Panel B: Growth Forecast and Dispersions										
Median Growth Forecast	0.25	0.17	0.15	0.15	0.16	0.16	0.16	0.17	0.17	0.2
Dispersion of Growth Forecast	0.81	0.52	0.44	0.41	0.42	0.41	0.4	0.39	0.39	0.45
Dispersion of Forecast	0.168	0.218	0.094	0.087	0.084	0.081	0.075	0.071	0.06	0.052
Dispersion of Forecast Error	0.64	0.65	0.58	0.55	0.53	0.51	0.47	0.4	0.39	0.3

Table 1.5.7. Announcement Period Returns

This table reports the returns for announcement and non-announcement periods across the profitability portfolios, as well as the corresponding proportions of late reports. The portfolios are value-weighted. The announcement period is defined as the three-day period from the day before the announcement to the day after the announcement. The first row reports the proportion of late reports. A report is considered late if it is released one week or more later than in the last fiscal year. The sample period is from July 1975 to December 2013.

	Profitability Portfolios									
	Low	2	3	4	5	6	7	8	9	High
Proportion of Late Reports (1 Week Later than Last Fiscal Year)	0.345	0.304	0.285	0.266	0.253	0.242	0.237	0.223	0.216	0.214
Total Return	-0.0055	0.038	0.106	0.0823	0.109	0.095	0.087	0.117	0.0817	0.0796
Announcement Period Return	-0.0041	-0.0002	0.0178	0.0067	0.0024	0.015	0.0044	0.0039	0.0115	0.017
Non-Announcement Period Return	-0.0015	0.0386	0.088	0.0756	0.107	0.08	0.0826	0.113	0.0702	0.0626
Announcement Return / Total Return	0.745455	-0.00526	0.167925	0.081409	0.022018	0.1578947	0.050575	0.033333	0.140759	0.213568

Table 1.5.8. Characteristics Across Portfolios

This table reports the firm characteristics for the ten decile portfolios sorted on operating profitability. Earnings yield is defined as the earnings per share divided by price. Net issuance is defined as the change in the natural logarithm of number of shares outstanding. Asset growth is defined as the change in the natural logarithm of assets per share outstanding. The sample excludes financial firms (those with one-digit standard industrial classification code of six). The sample period is from July 1963 to December 2013.

	Profitability Portfolios									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Firm Characteristics										
Net Issuance	0.179	0.086	0.068	0.067	0.06	0.056	0.059	0.069	0.057	0.066
Size	285	1112	875	958	1139	1348	1614	1910	2254	2909
Book-to-Market	1.076	1.25	1.14	1.04	0.952	0.853	0.757	0.671	0.577	0.416
Asset Growth	-0.021	0.054	0.065	0.064	0.071	0.08	0.085	0.081	0.103	0.14
Earnings Yield	-0.387	-0.023	0.026	0.048	0.051	0.065	0.073	0.061	0.071	0.06
Mean Firm Age	9.57	15.36	16.78	16.62	16.58	16	15.62	15.17	14.2	11.56
Median Firm Age	5.6	10	11	11	11	10.6	10.5	10.3	9.6	7.3
Panel B: Distress Measures										
Ohlson O-score	1.69	0.15	0.13	0.11	0.09	0.08	0.06	0.06	0.06	0.11
EDF	0.197	0.138	0.111	0.089	0.078	0.066	0.056	0.048	0.042	0.038
Downgrade	1.81	1.53	1.49	1.31	1.32	1.07	1.13	1.04	0.96	1.06
Default	0.44	0.18	0.11	0.1	0.04	0.03	0.04	0.05	0.03	0.03

Table 1.5.9. Sales and Earnings Pattern

This table reports the stock return, sales and earnings trend across the profitability portfolios. Panel A shows the past one year, past five year, future one year, and the future five year return of the ten decile portfolios sorted on operating profitability. Panel B shows the trend in past five year and future five year sales growth and earnings per share growth. The trend is calculated by fitting a least squares growth line to the logarithms of the six annual observations from year t-5 to year t. Only observations with at least 5 years of data are kept. The sample excludes financial firms (those with one-digit standard industrial classification code of six). The sample period is from July 1963 to December 2013.

	Profitability									
	Low	2	3	4	5	6	7	8	9	High
Panel A: Return										
Past 1 Year Return	0.055	0.124	0.154	0.159	0.174	0.178	0.198	0.206	0.21	0.252
Past 5 Year Return	0.158	0.503	0.664	0.833	0.94	1.06	1.2	1.386	1.64	2.277
Future 1 Year Return	0.074	0.145	0.168	0.164	0.167	0.17	0.161	0.17	0.168	0.185
Future 5 Year Return	0.828	1.06	1.052	1.058	0.99	1.02	0.99	1	1.04	1.07
Dispersion of Future 1 Year Return	0.95	0.68	0.72	0.63	0.58	0.61	0.56	0.61	0.6	0.74
Dispersion of Future 5 Year Return	3.04	2.68	2.53	2.51	2.17	2.25	2.26	2.69	3.2	3.36
Panel B: Sales and EPS Growth										
Past 5 Year Sales Growth	0.0213	0.0312	0.0348	0.0315	0.0324	0.0322	0.033	0.034	0.034	0.0405
Future 5 Year Sales Growth	0.0269	0.0202	0.0228	0.0221	0.0206	0.0206	0.0221	0.0224	0.0232	0.0247
Dispersion of Future Sales Growth	0.27	0.16	0.14	0.13	0.12	0.12	0.12	0.12	0.12	0.15
Past 5 Year EPS Growth	-0.0184	-0.0121	-0.0052	-0.00028	0.0059	0.0134	0.0153	0.0154	0.02	0.0244
Future 5 Year EPS Growth	0.0306	0.0237	0.0116	0.0032	-0.0004	-0.0023	-0.0029	-0.0059	-0.0082	-0.0105
Dispersion of EPS Growth	0.3	0.25	0.21	0.21	0.22	0.2	0.2	0.2	0.19	0.19

Table 1.5.10. Portfolio Double Sorts

This table reports descriptive statistics of portfolio double sorts based on operating profitability and analyst growth forecast. The portfolios returns are value-weighted and sorted based on NYSE breakpoints. It shows the monthly return in percentage, the operating profitability, the median growth forecast, and the forecast errors for each of the 25 double-sorted portfolios. The sample excludes financial firms (those with one-digit standard industrial classification code of six). The period is from July 1975 to December 2013.

	Profitability					
	1	2	3	4	5	Difference
Median Forecast Growth	**Returns**					
1	0.91	0.97	0.97	1.2	1.2	0.29
2	1.2	1.1	1	1.2	1	-0.2
3	0.98	0.85	1.2	1.1	0.98	0
4	0.87	1.2	0.71	0.98	1	0.13
5	0.19	0.94	0.74	0.99	1.3	1.11
Difference	0.72	0.03	0.23	0.21	-0.1	

	Profitability					
	1	2	3	4	5	Difference
Median Forecast Growth	**Forecast Error**					
1	0.33	0.13	0.14	0.23	0.09	-0.24
2	0.27	0.17	0.12	0.08	0.07	-0.2
3	0.31	0.13	0.11	0.08	0.03	-0.28
4	0.06	0.13	0.07	0.07	0.03	-0.03
5	0.15	0.09	0.07	0.04	0.03	-0.12
Difference	0.18	0.04	0.07	0.19	0.06	

	Profitability				
	1	2	3	4	5
Median Forecast Growth	**Forecast Growth**				
1	0.04	0.05	0.05	0.06	0.05
2	0.1	0.1	0.1	0.1	0.1
3	0.13	0.13	0.13	0.13	0.13
4	0.16	0.16	0.16	0.16	0.16
5	0.34	0.27	0.26	0.25	0.26

	Profitability				
	1	2	3	4	5
Median Forecast Growth	**Profitability**				
1	0.047	0.114	0.147	0.188	0.293
2	0.043	0.113	0.148	0.188	0.28
3	0.054	0.115	0.149	0.191	0.286
4	0.036	0.114	0.148	0.192	0.3
5	-0.026	0.114	0.148	0.191	0.321

CHAPTER 2

Flexible Price and Leverage

2.1. Introduction

Understanding firms' capital structure is perhaps the central question in corporate finance. This paper argues that the frequency with which firms adjust product prices can help us understand persistent differences in financial leverage across firms (Lemmon, Roberts and Zender (2008), DeAngelo and Roll (2015)). We test whether firms' inability to adjust output prices to aggregate and idiosyncratic shocks exposes them to financial constraints, and hence reduces leverage.

Price rigidity—the fact that firms do not adjust prices to macroeconomic shocks—has long been a focus in Macroeconomics and Industrial Organization. We build on the evidence of persistent heterogeneity in the firm-level frequency of price adjustment across and within industries (Nakamura and Steinsson (2008) and Gorodnichenko and Weber (2015)). Golosov and Robert (2007) and Alvarez et al. (2011) show the frequency of price adjustment changes little over time, even with inflation rates ranging from 0 to 16 percent. Weber (2015) documents the correlation between price rigidity, exposure to aggregate risk, and the cross section of stock returns. Firm-level price rigidity is highly persistent and a source of systematic risk, making it a viable candidate to explain the capital structure of firms.

To guide our empirical analysis, we develop a costly-state-verification model, in which firms adjust prices imperfectly to macroeconomic shocks. Firms with inflexible prices are more exposed to aggregate shocks, and hence their profits are more volatile. Our contribution is proposing price inflexibility as an economically motivated driver of profit volatility. Because of higher profit volatility, inflexible-price firms face more binding financial constraints. In the model, bank lending relaxes financial constraints by providing a monitoring technology.

The model predicts that inflexible-price firms have unconditionally lower financial leverage than flexible-price firms. Moreover, a shock to the availability of bank debt increases the leverage of inflexible-price firms more than the leverage of flexible-price firms. Empirically, uncertainty about the price level and the role of price-setting frictions is most relevant for profits over long horizons. In our baseline analysis, we therefore test these predictions using long-term leverage as the outcome variable, as opposed to short-term leverage.

We start our empirical analysis documenting a novel stylized fact consistent with the model's predictions, that is, flexible-price firms have higher financial leverage than inflexible-price firms. We document this fact using the confidential micro data underlying the official producer price index (PPI) of the Bureau of Labor Statistics (BLS). We observe monthly good-level pricing data for a subsample of the S&P500 firms from January 1982 to December 2014.

Our preferred leverage measure—the long-term debt to assets ratio—is 4 percentage points higher for the most flexible-price firms than for most inflexible-price firms, which is 19% of the average ratio in the sample. A two standard-deviation increase in our continuous measure of price flexibility is associated with 2.5 percentage-point higher long-term debt to assets ratio, which is 12% of the average ratio in the sample. We estimate these magnitudes after partialling out known determinants of capital structure such as size, tangibility, profitability, and the book-to-market ratio. We also control for industry concentration and for firm-level measures of market power, which might be correlated with the degree of price flexibility of firms. Moreover, these results only exploit the variation in price flexibility within industries and within years. The size of the estimated coefficients is similar if we use the errors-in-variables estimator based on linear cumulant equations of Erickson, Jiang and Whited (2014). The size of the estimated effect doubles if we do not limit the variation of price flexibility within industries. This result is consistent with the fact that price flexibility varies substantially both within and across industries.

A crucial feature of our model is that inflexible-price firms are riskier borrowers, because their profits are more volatile. We show that firms with inflexible prices are more likely to default compared to flexible-price firms. This fact adds to previous findings that firms with inflexible product prices have more volatile cash flows after monetary policy shocks, and have higher total and idiosyncratic stock return volatility (Gorodnichenko and Weber (2015) and Weber (2015)). To assess whether the effect of price flexibility on leverage is causal, one route would be testing the effect of a shock to firm-level price flexibility on leverage. But price flexibility is a highly persistent characteristic of firms (see Nakamura and Steinsson (2008), Golosov and Robert (2007), and Alvarez et al. (2011)). For instance, in our sample, a firm-level regression of post-1996 price flexibility onto pre-1996 price flexibility yields a slope coefficient of 93%. This persistence implies we cannot consider a shock to firm-level price flexibility for identification purposes.

We therefore propose an identification strategy derived from our model's predictions, and in line with the financial constraints literature. We (i) identify a shock to the availability of bank capital to firms; (ii) show the most constrained firms increase leverage more than the least constrained firms; (iii) show the change does not revert in the short run.

We use the staggered state-level implementation of the Interstate Banking and Branching Efficiency Act (IBBEA) between 1994 and 2005 (Rice and Strahan (2010) and Favara and Imbs (2015)) to show that inflexible-price firms are more exposed to financial constraints. Restrictions on U.S. banks' geographic expansion date back at least to the 1927 McFadden Act, but the IBBEA of 1994 let bank holding companies enter other states and operate branches across state lines. The step-wise repeal of interstate bank branching restrictions increased the supply of credit. Banking deregulation results in lower interest rates charged (Jayaratne and Strahan (1996)), more efficient screening of borrowers (Dick and Lehnert (2010)), increased spatial diversification of borrowers (Goetz, Laeven and Levine (2013)), higher loan volume (Amore, Schneider and Zaldokas (2013)), more credit cards (Kozak and Sosyura (2015)), and increased lending to riskier firms (see Neuhann and Saidi (2015)).

We interpret the staggered state-level implementation of the IBBEA as a positive shock to banks' monitoring effectiveness, which is exogenous to the individual firms' financial decisions. After the deregulation, large banks branched across states, and were able to lend to local firms. We therefore propose a triple-differences identification strategy. We compare outcomes within firms before and after the implementation of the IBBEA in the state where the firms operate, across firms in states that deregulated or not, and across flexible- and inflexible-price firms. Firms in states that did not deregulate act as counterfactual for the evolution of the long-term debt of treated firms absent the shock. We show that before the shock the trends of long-term debt of flexible- and inflexible-price firms are parallel, and that the price flexibility of firms does not change around the shock.

Consistent with our model's predictions, inflexible-price firms increased their leverage more than flexible-price firms after the deregulation. Crucially, the effect is driven by inflexible-price firms with lower a cash-to-assets ratio, which were more likely to need external capital to fund their operations. The most flexible-price firms keep their leverage virtually unchanged after the deregulation.

The availability of product pricing micro-data requires we focus on large firms. It might appear surprising that these firms depend on bank credit, but we find 95% of the firms in our sample have credit lines with at least one bank by using data from Sufi (2009). The average rate of utilization is above 20%, which suggests bank relationships are relevant in our sample. Moreover, both the likelihood of having credit lines and their sizes increase after the implementation of the IBBEA. Consistent with our results on leverage, the increase in the size of credit lines is mainly driven by inflexible-price firms.

We corroborate our triple-differences results in a quadruple-differences setting, which allows the construction of falsification tests. We split states into early deregulators (between 1996 and 1998) and late deregulators (after 2000). We first replicate our results comparing flexible- and inflexible-price firms in early and late deregulators, before and after 1996, but only using observations prior to 2000, when late deregulators had not yet implemented the IBBEA. The effects of the deregulation on capital structure are driven by inflexible-price firms in early deregulation states, as opposed to inflexible-price firms in late deregulation states and flexible-price firms in all states.

In the first falsification test, we repeat the analysis using only observations prior to 1996, when no state had yet deregulated. We use 1992 as a placebo implementation date for early deregulators, which is four years before 1996. We do not find any difference in the capital structure of inflexible-price firms in early states compared to inflexible firms in late states before and after 1992. Instead, we corroborate the baseline finding that flexible-price firms have higher long-term debt than inflexible-price firms at any point in time, irrespective of their state.

In the second falsification test, we repeat the analysis using only observations prior to 1996 and after 2000. Before 1996, no states had yet deregulated, and after 2000, all states had deregulated. Consistent with our interpretation of the shock and our model's predictions, inflexible-price firms in both early states and late states have higher long-term debt after 2000 compared to before 1996, whereas flexible-price firms in both sets of states do not change their capital structure after 2000.

Our paper adds to a recent literature studying the macroeconomic determinants of financial leverage, default risk, and bond yields. Bhamra, Kuehn and Strebulaev (2010) study the effect of time-varying macroeconomic conditions on firms' optimal capital structure choice. Kang and Pflueger (2015) show that fear of debt deflation is an important driver of corporate bond yields. Favilukis, Lin and Zhao (2015) document that firms with higher wage rigidities have higher credit risk. Labor market frictions vary at the industry level, and hence cannot account for our findings.

2.2. Theoretical Framework

We consider the optimal financing decision of a firm in a one-period partial equilibrium setup with costly state verification (Townsend (1979), Gale and Hellwig (1985)). This stylized model allows us to compare two financing environments. First, the firm borrows through the public bond market. Second, the firm borrows from a bank. Owners of diffusely-owned public bonds might suffer a coordination problem when monitoring private information (Diamond (1991a), Diamond (1991b)). Banks have access to a costly monitoring technology, which distinguishes them from the public bond market.

The model generates two main predictions. First, inflexible-price firms have lower leverage than flexible-price firms. Second, inflexible-price firms increase leverage more than flexible-price firms in response to an increase in monitoring effectiveness.

In the model, firms differ in their ability to adjust output prices to macroeconomic shocks. Inflexible-price firms have greater uncertainty about profits. Their profits are identical to those of flexible-price firms when realized inflation coincides with expected inflation. However, inflexible-price firms have lower profits when realized inflation is either unexpectedly high or unexpectedly low.

Inflexible-price firms have an incentive to report low profits even when profits are high, which limits their debt capacity. Monitoring reduces the incentive to misreport profits, and allows inflexible-price firms to credibly pledge a greater share of real profits to lenders. Bank lending can therefore mitigate credit constraints faced by inflexible-price firms.

Within the model, we interpret the implementation of IBBEA as an improvement in banks' monitoring effectiveness, or equivalently the likelihood of correctly auditing firm profits. This interpretation can be justified if there is heterogeneity across banks' skills in monitoring a specific firm from a specific industry. In that case, an increase in the set of potential lenders will improve the quality of the eventual bank-firm match.

Production and Prices. We use capital letters to denote levels and small letters to denote logs. The firm's actual price level may differ from the optimal price if the firm can update prices or information only infrequently (Calvo (1983), Mankiw and Reis (2002)). We denote the log difference between actual and optimal product prices by Δp.

For simplicity, the price gap can take three values with associated probabilities

$$Prob\,(\Delta p = 0) = \pi_0, \tag{2.2.1}$$

$$Prob\,(\Delta p = h) = \frac{\pi_h}{2}, \tag{2.2.2}$$

$$Prob\,(\Delta p = -h) = \frac{\pi_h}{2}, \tag{2.2.3}$$

$$\pi_0 + \pi_h = 1. \tag{2.2.4}$$

The expected price gap is zero. The parameter h captures how far the firm allows prices to deviate from the optimum when there are shocks to the aggregate price level. The parameter h is a reduced form to model pricing frictions which might originate from costs of price adjustment, managerial costs, information processing costs, or negotiation costs. Zbaracki et al. (2004) shows that a U.S. manufacturing firm with annual revenues of more than \$1bn. spend about 1.2% of annual revenues on price adjustments, which corresponds to about 20% of the net profit margin. Gorodnichenko and Weber (2015) calibrate their fully dynamic model to the micro-data underlying the PPI and find similar costs of price adjustments.

In New Keynesian models with partially monopolistic competition, price dispersion leads to production misallocations and real economic costs (Woodford (2003)). When the price gap is negative, firm revenue per unit sold and total firm profits are below the optimum. When the price gap is positive, high prices reduce demand, and firm profits are also below the optimum.

We capture the key features of costly price dispersion with a simple, quadratic profit function. The profit function is maximized at $\Delta p = 0$, ensuring existence of a flexible-price equilibrium in which all firms charge the same price. Firm profits scale with firm capital K, giving firm profits as

$$Profit_{\Delta p} = K \times R_{\Delta p}, \tag{2.2.5}$$

$$R_{\Delta p} = exp\,(r_{\Delta p})\,, \tag{2.2.6}$$

$$r_{\Delta p} = \bar{r} - a(\Delta p)^2. \tag{2.2.7}$$

Here, $\bar{r} > 0$ and $a > 0$ are constants, reflecting log returns when the price gap is zero and the curvature of the profit function. $\bar{r} > 0$ is needed to ensure a positive net present value return on capital. Equation (2.2.5) obtains as a second order approximation around the optimal price in a micro-founded model. The model predictions do not rely on the specific functional form (2.2.5) through (2.2.7). Instead, we rely on a quadratic profit function to maximize clarity of exposition.

The Financing Problem. The owner of the firm has personal wealth or equity, E, which determines the scale of the firm. The owner has all bargaining power, and the lender breaks even in expectation. The interest rate in the economy is zero, and the owner and the investor are both risk neutral. The total capital of the firm is the sum of debt and equity,

$$K = D + E. \tag{2.2.8}$$

We make two additional assumptions to make the financing problem interesting. First, we assume the project's net present value is positive, that is,

$$\pi_0 R_0 + \pi_h R_h > 1. \tag{2.2.9}$$

Here, $R_0 = exp(r_0)$ and $R_h = exp(r_h)$. Second, we assume the firm's returns are less than 1 in the low-profit state,

$$R_h < 1. \tag{2.2.10}$$

Lenders cannot observe firm profits. This assumption captures the idea that lenders cannot costlessly observe firms' optimal and actual pricing strategies. The manager's incentive to misreport realized profits constrains the set of feasible financing contracts. Contracts in our model are real to focus on the cross-sectional implications of the model. With nominal contracts, uncertainty about the aggregate price level can further lower the debt capacity of both inflexible- and flexible-price firms (Fisher (1933), Bhamra, Fisher and Kuehn (2011), Kang and Pflueger (2015)).

Solution without Monitoring. First, we consider the optimal debt contract when no monitoring technology is available. We can think of this setup as a firm that can only borrow from public debt markets.

The optimal contract must satisfy the revelation principle: the borrower reveals her profits truthfully. Without monitoring technology, the optimal financing contract requires constant payments across states. Otherwise, the borrower has an incentive to lie about profits. The project has a positive net present value and the manager optimally borrows the maximum amount that the lender is willing to lend. Optimal leverage follows from the lender's break-even constraint:

$$\frac{D}{K} = R_h. \tag{2.2.11}$$

Firms with more inflexible prices, that is, larger h, have lower returns R_h, and hence lower leverage.

Solution with Monitoring. Next, we consider the case in which the lender can access a costly monitoring technology. This setup resembles a firm that borrows from a bank, which has a costly technology to monitor the manager's activities.

Monitoring costs are proportional to firm size, and are given by γK. Monitoring larger firms requires more effort than monitoring smaller firms. Monitoring is successful with probability ρ, in which case the lender learns the true level of profits. When monitoring is unsuccessful, the lender acquires no information about firm profits.

Let C_0 denote the manager's consumption in state 0. The manager's optimal consumption in state h is zero, which minimizes incentives to misreport firms profits in state 0.

The optimal contract maximizes the manager's expected consumption,

$$V = \pi_0 C_0, \tag{2.2.12}$$

subject to the following incentive-compatibility constraints:

$$C_0 \geq (1-\rho)K(R_0 - R_h), \tag{2.2.13}$$

$$C_0 \leq K\left(R_0 - R_h\right). \tag{2.2.14}$$

Constraint (2.2.13) says the manager has no incentive to lie when the true state is 0. Constraint (2.2.14) says the manager has no incentive to lie when the true state is h. The bank's break-even constraint is

$$D = \pi_h K(R_h - \gamma) + \pi_0(KR_0 - C_0). \tag{2.2.15}$$

Constraint (2.2.13) must hold with equality for the optimal contract. Solving for the optimal leverage ratio gives

$$D/K = R_h + \rho\pi_0(R_0 - R_h) - \pi_h\gamma. \tag{2.2.16}$$

When monitoring is completely ineffective ($\rho = 0$) and free ($\gamma = 0$), (2.2.16) reduces to the case without monitoring technology (see equation (2.2.11)).

Model Predictions. We interpret the staggered implementation of the IBBEA from 1994 to 2005 as a shock to ρ, the banks' probability of learning the true level of profits when monitoring. Expression (2.2.16) implies the following testable predictions.

PREDICTION 1. *Inflexible-price firms have lower leverage than flexible-price firms.*

The expression for leverage (2.2.16) increases with firm's profits in the low-profit state, R_h. Since inflexible-price firms have lower R_h, leverage decreases with price inflexibility h.

PREDICTION 2. *Following an increase in the effectiveness of monitoring, inflexible-price firms increase leverage more than flexible-price firms.*

Higher price inflexibility h implies a larger gap between high and low profits, $R_0 - R_h$. Expression (2.2.16) then implies that leverage increases more in monitoring effectiveness ρ for inflexible-price firms than for flexible-price firms.

2.3. Data

Financial Data. We focus on firms which have been part of the S&P500 during our sample period from January 1982 to December 2014 due to the availability of the PPI micro-data to construct measures of price rigidities at the firm level.[1] The S&P500 contains large U.S. firms and captures approximately 80% of the available stock market capitalization in the U.S., therefore maintaining the representativeness for the whole economy in economic terms. The BLS samples establishments based on value of shipments, and we have a larger probability of finding a link between BLS pricing data and financial data when we focus on large firms.

We have 1,195 unique firms in our sample due to changes in the index composition during

[1] Gorodnichenko and Weber (2015), Weber (2015), and Jaimovich, Rebelo and Wong (2015) have used similar data.

the sample period, out of which we were able to merge 469 with the BLS pricing data.

Stock returns and shares outstanding come from the monthly stock return file from the Center for Research in Security Prices (CRSP). Financial and balance-sheet variables come from Compustat. $Lt2A$ is defined as long-term debt to total assets; $Prof$ is operating income over total assets; $size$ is the log of total assets; BM is the book-to-market ratio; $It2A$ is intangible assets defined as total assets minus the sum of net property, plant, and equipment, cash and short-term investments, total receivables, and total inventories to total assets; PCM is the price-to-cost margin defined as ratio of net sales minus costs of goods sold to net sales; and HHI is the Herfindahl-Hirschman index of sales at the Fama & French 48 industry level.

We follow Lemmon, Roberts and Zender (2008) and Graham, Leary and Roberts (2014) in the choice and definition of capital structure determinants. To reduce the effects of outliers, we winsorize all variables at the 1 and 99 percentile.

Micro Pricing Data. We use the confidential micro pricing data underlying the PPI from the BLS. We have monthly price information for individual goods from 1982 to 2014. The BLS defines prices as "net revenue accruing to a specified producing establishment from a specified kind of buyer for a specified product shipped under specified transaction terms on a specified day of the month." Unlike the Consumer Price Index (CPI), the PPI measures the prices from the perspectives of producers. The PPI tracks prices of all goods-producing industries such as mining, manufacturing, and gas and electricity, as well as the service sector.[2]

The BLS uses a three-stage procedure to construct their sample of products. First, it compiles a list of all firms filing with the Unemployment Insurance system to construct the universe of all establishments in the United States. Then, the BLS probabilistically selects sample establishments and goods based on the total value of shipments or on the number of employees. The final data set covers 25,000 establishments and 100,000 individual items. Prices are collected through a survey, with is emailed or faxed to participating establishments. Individual establishments remain in the sample for an average of seven years, until a new sample is selected to account for changes in the industry structure.

To compute our measure FPA, we first calculate the frequency of price adjustment at the good level as the ratio of price changes to the number of sample months. For example, if an observed price path is \$4 for two months and then \$5 for another three months, one price change occurs during five months and the frequency is 1/5. We exclude price changes due to sales.[3] We then equally weight and aggregate the frequencies to the establishment level via internal identifiers of the BLS. To perform the firm-level aggregation, we check whether establishments with the same or similar names are part of the same company. In addition, we use publicly available data to search for names of subsidiaries and name changes due to, for example, mergers, acquisitions, or restructuring occurring during the sample period for

[2]The BLS started sampling prices for the service sector in 2005. The PPI covers about 75% of the service sector output.

[3]This assumption is standard in the literature and does not change results, as sales are rare in the PPI micro-data. See Gorodnichenko and Weber (2015).

all firms in the data set.[4]

The granularity of the data at the firm level allows us to differentiate the effect of price flexibility from that of other industry- and firm-level characteristics.

Price stickiness of similar firms operating in the same industry can be different. This difference can arise due to different costs of negotiating with customers and suppliers, the physical costs of changing prices, or the managerial costs such as information gathering, decision making, and communication (see Zbaracki et al. (2004)).

Descriptive Statistics. Panel A of Table 2.5.1 reports descriptive statistics for our running sample. Firms in our sample do not adjust their output prices for roughly seven months ($-1/(log(1-FPA))$) with substantial variation across firms as indicated by the large standard deviation. The average long-term leverage ratio $Lt2A$ is around 21%. Firms have an operative income margin ($Prof$) of 15%. 21% of assets are intangible ($It2A$). The average book-to-market ratio is 60% (BM) and the average firm size is USD 3.8 bn. ($size$). The average price-to-cost margin (PCM) is 37%, and average industry concentration (HHI) is 0.11. Panel B of Table 2.5.1 reports correlations of the variables.

Flexible-price firms have unconditionally higher long-term leverage and the frequency of price adjustment is unconditionally correlated with standard determinants of capital structure. The frequency of price adjustment is lower in more concentrated industries and for firms with high markups and might, therefore, reflect more market power on the side of firms.

Are Inflexible-price Firms Riskier? When firms cannot adjust prices to changing market conditions, cashflow and profit volatilities increase, increasing default risk for a given leverage ratio. To assess the relation between price stickiness and default rates empirically, we obtain default and credit rating information from Moody's Default and Recovery Database (DRD) and match it to firms in our sample. We construct five default indicator variables $Default_{t+s}$ for s running from 1 to 5. This dummy is equal to 1 if there is at least one default within the next $t+s$ years, and 0 otherwise.

Table 2.5.2 proposes logistic regressions of default probabilities on the frequency of price adjustment, controlling for firm leverage. Higher leverage is associated with higher default rates. Controlling for leverage, we see that firms with more flexible output prices are less likely to default. The relation between FPA and two- to five-year default rates is statistically significant. The stronger predictive power for multi-year default probabilities is consistent with our observation that uncertainty about the aggregate price level, and hence price rigidities, are likely more relevant over multi-year time horizons.

Financial Dependence and Bank Debt. Our sample includes firms in the S&P500 from January 1982 to December 2014, for which we can observe the micro-pricing data. Because our model and our empirical application exploit a shock to bank-level debt, we need to verify that the firms in our sample depend on bank debt rather than only public bond markets. Colla et al. (2013) report that bank loans and credit lines jointly make up at least

[4] See Weber (2015) for a more detailed description of the data and construction of variables.

30% of leverage for the largest Compustat firms, suggesting that bank debt is indeed an important source of financing for firms with similar characteristics to ours.

To assess whether the firms in our sample depend on bank debt, we use the data on credit lines collected by Sufi (2009).[5] These data allow observing an extensive margin of credit lines—whether firms have an active credit line or not—and an intensive margin of credit lines, the share of the line which has been used at each point in time. We can construct the extensive margin for all the firm-year observations in our sample, whereas the intensive margin is only available for those firms that match with the 5% random sample of Compustat firms constructed by Sufi (2009).

As for the extensive margin, the vast majority of the firm-year observations in our sample have a credit line open with at least on bank (94.6%). Consistent with our model's prediction, we find that flexible-price firms are more likely to have a credit line (97.3%) than inflexible-price firms (93.6%), and a t-test for whether these ratios are equal rejects the null at the 1% level of significance. Moving on to the intensive margin, we find that the usage rate of credit lines for firms in our sample is 24.8%. There is an economically significant difference in the usage rate across inflexible-price firms (28.1%) and flexible-price firms (15.6%). A t-test for whether these ratios are equal rejects the null at the 5% level of significance. In Figure A.1 of the Online Appendix, we plot the density of the usage ratio for the two groups of firms. The full distribution of the usage ratio for inflexible-price firms lies to the right of the distribution for flexible-price firms. Although inflexible-price firms are less likely to have a credit line with banks, they are more likely to draw down the credit line, indicating that they might be more credit constrained than flexible-price firms.

2.4. Baseline Analysis

Price Flexibility and Leverage. We move on to investigate the empirical relationship between leverage and price stickiness. Inflation is highly persistent (Atkeson and Ohanian (2001), Stock and Watson (2007)), and uncertainty about the aggregate price level increases with the forecast horizon. Price-setting frictions should therefore be most relevant for profits over long horizons. In addition, Heider and Ljungqvist (2015) argue that firms use short-term leverage to finance working capital, and are therefore unlikely to change short-term leverage in response to changing tax benefits or credit supply. For these reasons, we focus on long-term debt, as opposed to short-term debt in our empirical analysis. In the Appendix, we replicate all the results using total debt as the outcome of interest. Most results are qualitatively similar, although the sizes of the associations are lower, consistent with the prediction that price-setting frictions are more relevant for profits over long horizons.[6]

Our most general specification is the following OLS equation:

$$Lt2A_{i,t} = \alpha + \beta \times FPA_i + X'_{i,t-1} \times \gamma + \eta_t + \eta_k + \epsilon_{i,t}, \tag{2.4.1}$$

[5] In contrast to Capital IQ, Sufi (2009) has comprehensive coverage starting in 1996 and information on drawn and undrawn credit lines.

[6] See Table A.3, Table A.4, and Table A.5 in the Appendix for the results using total debt.

where $Lt2A_{i,t}$ is long-term debt to assets of firm i in year t; FPA is the frequency of price adjustment, which is higher for firms with more flexible prices; X is a set of standard determinants of capital structure; η_t is a set of year fixed effects, which absorb time-varying shocks faced by all firms, such as changes in economy-wide interest rates; η_k is a set of industry fixed effects, which absorb time-invariant unobservable characteristics that differ across industries. We use two definitions of industry fixed effects. The coarser definition allows for variation within 1-digit SEC codes, which splits the firms in our sample into 8 industry groups. The tighter definition allows for variation within the 48 Fama-French industries. Across all specifications, we cluster standard errors at the firm level to allow for correlation of unknown form across the residuals of each firm over time.

Table 2.5.3 displays the baseline results. In columns (1)-(3), FPA is the continuous measure of price flexibility, whereas in columns (4)-(6), it is a dummy variable that equals 1 for the firms in the top 25% of the distribution based on price flexibility, and 0 for the firms in the bottom 25% of the distribution.

In column (1) of Table 2.5.3, we regress the long-term debt to assets ratio on price flexibility and standard determinants of capital structure. Firms with more flexible output prices have a higher ratio of long-term debt over total assets. This positive association is significantly different from 0 at the 1% level of significance. A one-standard-deviation increase in price flexibility (0.14) is associated with 2.1-percentage-point increase in the long-term debt to assets ratio, which is 10% of the average ratio in the sample. In columns (2)-(3), we only exploit variation in the frequency of price adjustment across firms within the same year, and across firms within the same industry, and we confirm the results in column (1).

In columns (3)-(6), we estimate the analogous specifications using the indicator for firms with the most flexible prices, and look only at the most flexible firms (top 25% of the distribution by price flexibility), and at the least flexible firms (bottom 25% of the distribution by price flexibility). We confirm the results we obtained with the continuous measure of price flexibility.[7] Being in the top quarter of the distribution of firms by price flexibility is associated with a 6-percentage-point higher ratio of long-term debt over assets. The results are qualitatively similar when we only exploit within-year and within-industry variation in price flexibility across firms.

Errors-in-Variables Specifications. Erickson, Jiang and Whited (2014) propose a novel methodology to account for measurement errors in explanatory variables using linear cumulant equations. They show several firm-level determinants of capital structure change sign or lose statistical significance once they correct for measurement errors. We follow their methodology to assess the robustness of the association between price flexibility and long-term leverage when correcting for measurement error in key variables. Specifically, we follow Erickson et al. (2014) assuming two key determinants of capital structure are possibly affected by measurement error: asset intangibility and the book-to-market ratio. In addition, we also assume the measure of price flexibility is measured with error. This assumption seems plausible, because the measure is based on the aggregation of frequencies of price adjustment

[7]The results are similar when we add all other firms and assign them a value of 0 for the FPA dummy measure.

at the good level based on a representative sample of goods. Note the errors-in-variables estimator we compute will therefore assume that the other variables in our specification are not measured with error.

In column (1) of Table 2.5.4, we report the baseline OLS estimator from column (1) of Table 2.5.3 to allow comparison across estimators. In columns (2)-(4), we report the estimated coefficients when implementing the cumulant-equation method of Erickson et al. (2014) for the third, fourth, and fifth cumulants. We do not report the results for using higher order cumulants in the linear equations, because of the size of our sample. Using higher order cumulants results in estimates of similar size but substantially lower standard errors. Comparing the estimated association of price flexibility with long-term leverage across specifications, the size and the significance of the coefficients is similar in the baseline OLS specification and when using the errors-in-variables estimator. The results for the other covariates are in general similar but some lose statistical significance or switch sign, including the two covariates we also assume are measured with error (book-to-market ratio and asset intangibility).

Identification Strategy and Falsification Tests. There is a positive association between the frequency of price adjustment at the firm level and firms' leverage ratios, measured as the amount of long-term debt over assets. In this section, we test whether these effects are causal.

To tackle this question, we need a shock to the financial constraints of inflexible-price firms, which is exogenous relative to the stock of long-term leverage. We also need a viable counterfactual or control group of firms to assess how inflexible firms' long-term leverage would have evolved absent the shock. The shock we use is the staggered state-level implementation of the Interstate Banking and Branching Efficiency Act (IBBEA) of 1994. The IBBEA represented a shock to the ability of banks to open branches and extend credit across state borders. This shock is relevant for the leverage of firms in our sample, because in section III.E we find that 95% of them have a credit line open with at least one bank, and such lines are used by all firms, especially by the inflexible-price firms.

Institutional Details. Restrictions to banks' geographic expansion have a long history in the U.S. (Kroszner and Strahan (2007)). The McFadden Act of 1927 gave states the authority to regulate in-state branching, and most states enforced restrictions on branching well into the 1970s. In 1970, only 12 states allow unrestricted in-state opening of branches and 16 states prohibited banks from opening more than a single branch. In addition to branching restrictions, the Douglas Amendment to the 1956 Bank Holding Company Act effectively prohibited a bank holding company from acquiring other banks outside the state where it was headquartered (Strahan (2003)).

Starting in the 1970s, the restrictions on acquiring banks across states were gradually eased. Kroszner and Strahan (1999) argue that the timing of this deregulation wave relates to the interaction of technological innovations, such as the ATM, with lobbying by large and well-capitalized banks, but not to time-varying local economic conditions.

The approval of IBBEA was a watershed event for interstate banking, but did not lead to nationwide branching in all states immediately. The law permitted states a) to require a minimum age of the acquired institution, b) to restrict *de novo* interstate branching, c) to disallow the acquisition of individual branches without acquiring the entire bank, and d) to impose statewide deposit caps. We use Rice and Strahan (2010)'s time-varying index for regulatory constraints between 1994 and 2005 to construct a dummy variable that equals 1 in the year when the state lifted at least one of the restrictions a) through d), and in all the subsequent years.[8]

Triple-Differences Strategy. We propose a triple-differences strategy. The Interstate Banking and Branching Efficiency Act (IBBEA) serves as a positive shock to the availability of loans and credit lines to riskier firms that were constrained before the deregulation. The state-level implementation of the 1994 repeal was staggered over the years, from 1996 to 2005. A group of states, which we label "early states," started to implement the deregulation between 1996 and 1998. Another groups of states, which we label "late states," only started to implement the deregulation after 2000. Our strategy exploits the time variation in the exposure to this shock firms faced based on their location. Moreover, we use the group of most flexible-price firms as a counterfactual for the evolution of long-term debt of inflexible price firms absent the deregulation shock. The idea is that the flexible-price firms were not borrowing constrained before 1996, because they were less risky compared to inflexible-price firms.

A necessary condition for identification is the *parallel trends assumption*, which states that the evolution of long-term debt of flexible- and inflexible-price firms before the deregulation was implemented in each state followed parallel trends, and hence after the deregulation was implemented in the state, the evolution of long-term debt of flexible-price firms represents a valid counterfactual to the evolution of long-term debt of inflexible-price firms had they not been exposed to the deregulation. We assess the plausibility of this assumption graphically in Figure 2.5.1. For ease of interpretation, Figure 2.5.1 plots the evolution of long-term debt for the two groups of early states, which deregulated after 1996 (top graph), and late states, which only deregulated after 2000 (bottom graph). In each graph, the blue solid line refers to the long-term debt to assets ratio of inflexible-price firms, which lie below the 25^{th} percentile of the distribution of price flexibility. The red dashed line refers to flexible-price firms, which lie above the 75^{th} percentile of the distribution of price flexibility. The black dotted line is the difference between the long-term debt to assets ratio of flexible- and inflexible-price firms.

As predicted by the model, firms with more inflexible prices have lower long-term debt to assets than firms with more flexible prices at any point in time. But this difference evolves over time. In the top graph, the difference is stable around a value of 10% before 1996, when early states started to implement the IBBEA, and hence the trends in long-term debt to assets appear to be parallel before 1996. Starting in 1996, though, the difference starts to decline until it reaches a value of 5% in 2006, which is half of the difference before 1996. This decline is driven by the fact that the leverage of inflexible-price firms increases more than that of flexible-price firms after 1996, which is consistent with the interpretation of the IBBEA implementation as a positive shock to the bank credit extended to riskier borrowers.

[8]No states re-instated any restriction they had already lifted. Several states lifted the restrictions a) through d) in different years, which, together with the staggered deregulation across states, might contribute to explain the slow convergence of long-term debt to assets of inflexible-price firms after 1996 (see Figure 2.5.1).

We observe similar patterns when looking at late states in the bottom graph, which only started to implement the IBBEA in 2000. Before 2000, the difference in the long-term debt to assets ratio across flexible- and inflexible-price firms is stable around a value of 14%, and hence the trends are parallel. After 2000, instead, this difference declines, until it reaches a value of 3% in 2006. The large increase in long-term debt to assets of inflexible-price firms after 2000 drives the convergence. The evolution of long-term debt to assets across states and firms with different levels of price flexibility appears consistent with the parallel-trends assumption which we need for identification.

A considerable body of research in macroeconomics finds the extent of price flexibility is a highly persistent feature of firms (e.g., see Golosov and Robert (2007) and Alvarez et al. (2011)). Ideally, we would like to test formally that the price flexibility of the firms in our sample did not change over time, and especially that it was not affected by the implementation of the IBBEA at the state level. The construction of the measure of price flexibility based on the BLS micro-pricing data does not allow computing yearly values, because we need to observe several price spells for a given good for the measure to be meaningful.

Therefore, we proceed as follows. We identify the firms in our sample for which we can observe monthly price spells for the three years before and after 1996. We construct a measure of price flexibility before 1996, based on the monthly spells in the period 1993-1995, and a measure of price flexibility after 1996, based on the monthly spells in the period 1996-1998. We then regress the post-1996 measure on the pre-1996 measure and a constant. Our null hypothesis is the regression coefficient equals 1, that is, the pre-1996 measure is perfectly correlated with the post-1996 measure. Our estimated coefficient equals 0.93, and we cannot reject the null that this coefficient differs from 1 at any plausible level of significance. The 95% confidence interval around the coefficient is (0.73; 1.12). Also note we truncate price spells by only focusing on a three-year period, and hence we introduce noise in our measures. The almost perfect correlation in the frequency of price adjustment before and after 1996 is therefore hardly consistent with the notion that firm-level price flexibility changed around the implementation of the IBBEA.

To implement our strategy, we estimate the following specification:

$$
\begin{aligned}
Lt2A_{i,t} &= \alpha + \beta \times FPA_i \times Deregulated_{i,t} \\
&\quad + \delta_1 \times FPA_i + \delta_2 \times Deregulated_{i,t} + \eta_t + \eta_f + \epsilon_{i,t},
\end{aligned}
\tag{2.4.2}
$$

where $Deregulated_{i,t}$ is an indicator that equals 1 if firm i is in a state that had implemented the deregulation in year t, and 0 otherwise; and η_t and η_f are a full set of year and industry fixed effects.

Equation (2.4.2) compares the long-term debt raised within firms before and after their state implemented the deregulation, across firms in deregulated and regulated states, and across flexible- and inflexible-price firms.

Based on our model, we have the following predictions on the coefficients in equation (2.4.2): $\delta_1 > 0$, because on average higher price flexibility leads to more long-term debt; and $\delta_2 \geq 0$, because firms have more funds available to borrow after the 1994 deregulation shock, which could be 0 because flexible-price firms were unlikely to be financially constrained before the shock. The crucial prediction of our strategy is that $\beta < 0$, because the most inflexible-price firms obtain disproportionally more funds after the deregulation compared to the most flexible-price firms.

Table 2.5.5 reports the estimates for the coefficients in equation (2.4.2). In columns (1)-(3), FPA is the continuous measure of price flexibility; in columns (4)-(6), it is the dummy that equals 1 for firms in the top 25% of the distribution based on price flexibility, and 0 for those in the bottom 25% of the distribution. For both sets of results, the first column reports estimates for the baseline specification. In the second column, we add year fixed effects and eight industry-level dummies, which capture the one-digit SIC industry to which the firm belongs. In the third column, we add year fixed effects and the forty-eight industry-level dummies for the Fama-French industry taxonomy.

Across all specifications, the sign of the estimated coefficients are in line with the predictions above. Firms with higher price flexibility have higher long-term debt on average ($\hat{\delta}_1 > 0$). More importantly, across all specifications, we find that flexible-price firms increase their leverage less than inflexible-price firms after the state-level implementation of the deregulation ($\hat{\beta} < 0$). The effect of the deregulation on the most flexible-price firms is close to zero, as can be seen by adding the estimates of $\hat{\beta}$ and $\hat{\delta}_1$ across all the specifications. Moreover, if we compare firms in deregulated and non-deregulated states after accounting for the effects of price flexibility and of the other firm-level determinants of capital structure, we do not find any difference in their long-term debt to assets ratio.

To corroborate the interpretation of the deregulation shock, we exploit the cross-sectional variation in terms of the financial dependence of firms. If the implementation of the IBBEA indeed increases the funds available to riskier firms, which have more inflexible prices, then inflexible-price firms that depend more on external financing to fund their operations should drive this effect. We thus estimate the specification in equation (2.4.2) separately for firms in the top tercile by cash-to-assets ratio and for other firms. The rationale is that inflexible-price firms with high cash-to-assets ratios will not depend much on external financing, whereas inflexible-price firms with lower cash-to-assets ratios should be those affected by the deregulation shock. Consistent with this interpretation, Table 2.5.6 shows that the effect of deregulation on firms' leverage is driven by inflexible-price firms with low cash-to-assets ratios (columns (1) and (3)), as opposed to those with high cash-to-assets ratios (columns (2) and (4)).

In the Appendix, we show that the results of our triple-differences specifications are robust across subsamples and using alternative definitions of price flexibility. Table A.1 in the Online Appendix replicates all the results when we exclude financial firms and utilities. Table A.2 estimates our main specification from equation (2.4.2) separately within one-digit SIC industries. The results are similar across all industries except utilities and finance.

Quadruple-differences and falsification tests. In order to further assess the validity and interpretation of our causal test, we propose an empirical setup that allows designing two falsification tests (Roberts and Whited, 2013). We exploit the fact that the state-level implementation of the IBBEA was not only staggered over time, but also clustered in two periods. The majority of U.S. states implemented the deregulation between 1996 and 1998. The second group of states, instead, only implemented the deregulation after 2000. We call the first group of states "early states," and the second group "late states." This setup allows us to construct three tests across three groups of years. Before 1996, no state had implemented the deregulation yet, which was only approved by the U.S. Congress in 1994. Between 1996 and 2000, firms in early states were exposed to the deregulation, but firms in late states were not exposed. After 2000, all firms were in states that had deregulated. Figure 2.5.2 gives a graphical depiction of this setup.

In a first specification, we corroborate our triple-differences result in the novel setup, by estimating the foll

(2.4.3)

$$\begin{aligned} Lt2A_{i,t} = {} & \alpha + \beta \times FPA_i \times After1996_{i,t} \times EarlyState_i + \delta_1 \times FPA_i \times After1996_{i,t} \\ & + \delta_2 \times FPA_i \times EarlyState_i + \delta_3 \times After1996_{i,t} \times EarlyState_i + \gamma_1 \times FPA_i \\ & + \gamma_2 \times After1996_{i,t} + \gamma_3 \times EarlyState_i + X'_{i,t} \times \zeta + \epsilon_{i,t}. \end{aligned}$$

Panel A of Figure 2.5.2 sketches the predictions of our model for the specification in equation (2.4.3). It is a quadruple-differences design, because it compares outcomes within firms before and after 1996, across firms before and after 1996, across firms in early and late states, and across flexible- and inflexible-price firms. To corroborate our earlier results, we estimate equation (2.4.3) only using firm-level observations up to 2000. The rationale is that firms in early states were exposed to the deregulation between 1996 and 2000, whereas firms in late states were not. Flexible- and inflexible-price firms in late states thus represent the control group for the differential evolution of long-term debt in flexible- and inflexible-price firms in early states, had they not been exposed to the deregulation shock.

Our prediction is that $\beta < 0$, $\delta_1 = 0$, and $\gamma_1 > 0$, that is, flexible-price firms have higher leverage on average, and after the deregulation, it is only inflexible-price firms in early states that increase their leverage compared to flexible price firms in early states, whereas the baseline effect of price flexibility on leverage does not change after 1996 for firms in late states.

The estimates in column (1) of Table 2.5.7 support our predictions. In columns (2)-(3) of Table 2.5.7, we repeat the analysis separately for firms with low and high cash-to-assets ratios. Similar to our earlier results, the effects are driven by the subsample of firms with higher need for external finance.

We then proceed to assess the validity of our designs by constructing two falsification tests. Panel B of Figure 2.5.2 sketches the predictions of our model for our first falsification test. We build on the specification in equation (2.4.3), but we limit our estimation to the firm-level observations before 1996. This limitation implies that no firm-level observations, either in early or late states, are exposed to the deregulation shock. Because in the baseline analysis we use a treatment period of four years for early states, from 1996 to 2000, we assign 1992 as a placebo deregulation year to observations in early states. We thus replace the dummy $After1996_{i,t}$ in equation (2.4.3) with the dummy $After1992_{i,t}$, which equals 1 for all firm-level observations after 1992. Our falsification test consists of comparing flexible- and inflexible-price firms in early and late states after 1992, and before the deregulation happened. If our earlier test was invalid, and our baseline results captured the effect of state-level characteristics different across early and late states, but unrelated to the deregulation event, we should reject the null hypothesis that $\beta = 0$. Columns (4)-(6) of Table 2.5.7 show that, instead, we fail to reject this null hypothesis at a plausible level of significance. As expected, we find that flexible-price firms have higher leverage on average, irrespective of the states where they are located.

Panel C of Figure 2.5.2 sketches the predictions of our model for our second falsification test, in which we exclude all firm-level observations between 1996 and 2000. This limitation implies that in each year, the observations in early and late years are either not exposed to the deregulation shock (before 1996), or they are all exposed to the deregulation shock (after 2000). We thus estimate the same specification in equation (2.4.3), but the new setup implies different predictions from those discussed above. On the one hand, we should not be able to reject the null that $\beta = 0$, because early and late states are exposed to the deregulation in the same years. On the other hand, we now do expect $\delta_1 < 0$ and $\gamma_1 > 0$, because flexible-price firms in both early and late states should have on average higher leverage, and should react less than inflexible-price firms to the deregulation shock. We find evidence consistent with these predictions in column (7) of Table 2.5.7, whereas columns (8)-(9) show the predictions go through for firms with higher need for external finance, but not for others, consistent with our interpretation of the deregulation shock.

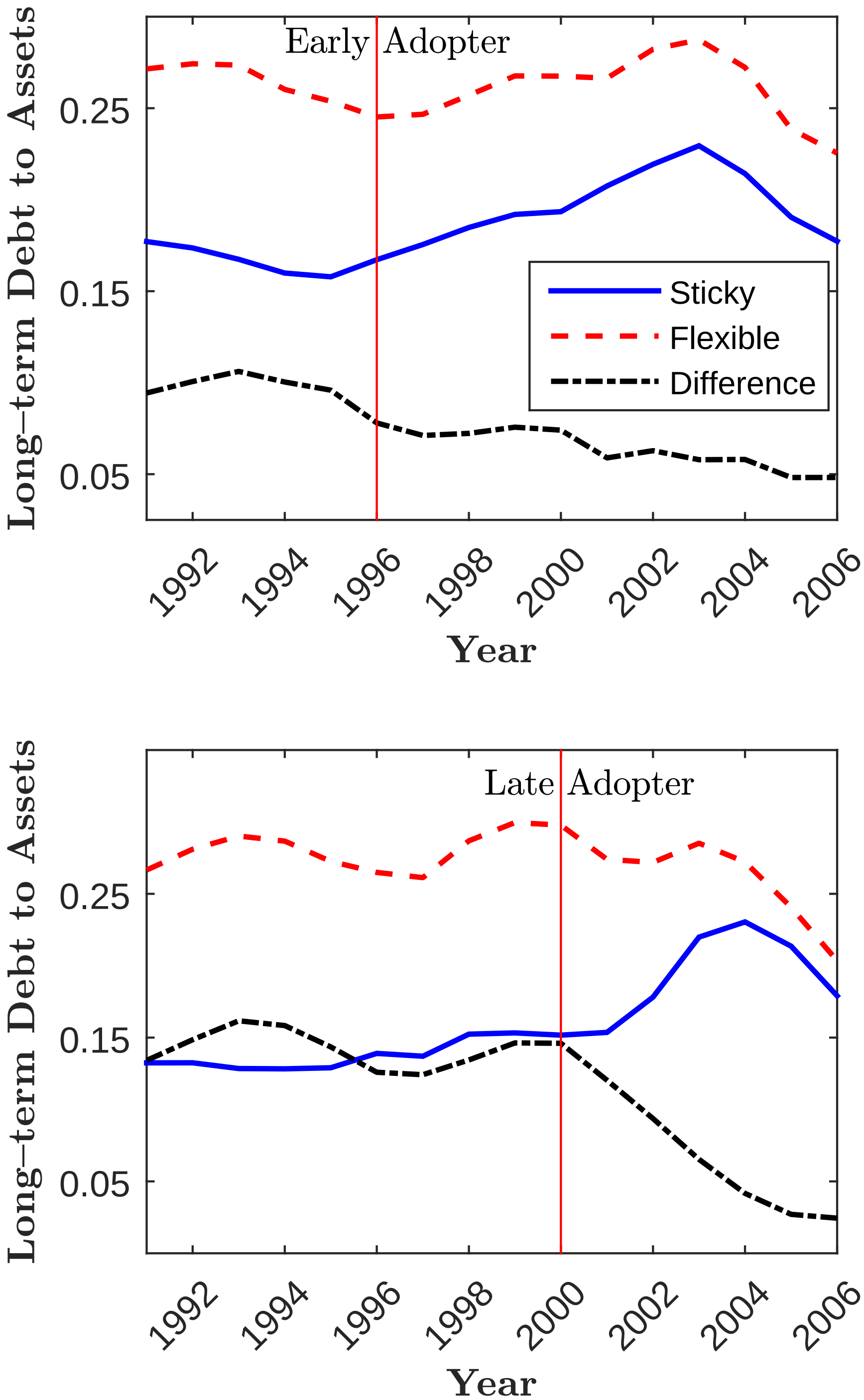
2.5. Conclusion

We show that firms with inflexible output prices have lower leverage relative to firms with flexible prices after controlling for standard determinants of capital structure choices. We test for the causality of the effect of price flexibility on leverage by exploiting the staggered state-level implementation of the 1994 Interstate Bank Branching Efficiency Act, which represented a shock to firms' access to bank debt, and hence to the financial constraints firms faced.

These findings are consistent with a simple costly-state-verification model in which inflexible-price firms cannot adjust their prices to macroeconomic shocks, and banks can access a costly monitoring technology. A central assumption of the model is that inflexible-price firms have higher volatility in real output prices, and are therefore riskier than flexible-price firms. We provide direct evidence using data from the Moody's Default database. Inflexible-price firms are more likely to default compared to flexible-price firms.

Price rigidity has a long tradition in research across fields as different as Marketing, Industrial Organization, and Macroeconomics. Our results show that the nominal rigidity of output prices plays an important role in understanding the persistent differences in financial leverage across firms. They open up exciting avenues for future research at the intersection of Corporate Finance, Macroeconomics, and Industrial Organization.

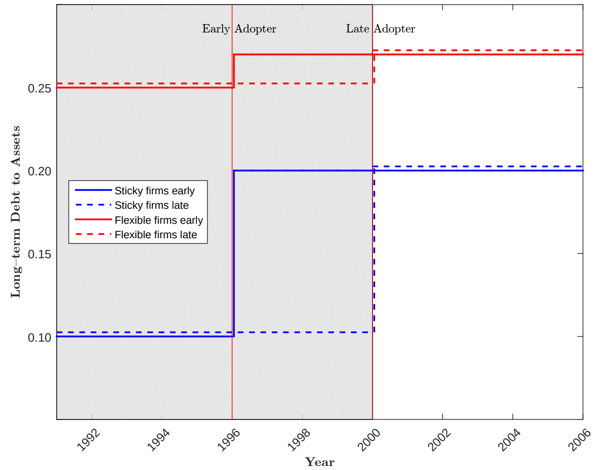
Figure 2.5.1. Long-Term Debt



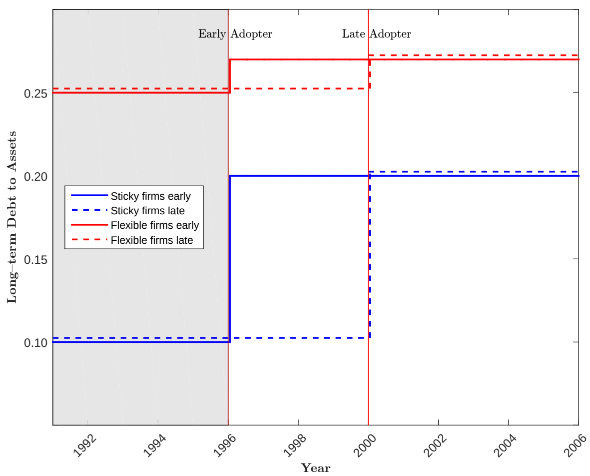
This figure plots long-term debt to total assets for different percentiles of the price stickiness distribution. Sticky firms are firms in the bottom 25th percentile of the distribution. Flexible-price firms are firms in the top 25th percentile of the distribution. Equally-weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. The sample period is January 1980 to December 2013.

Figure 2.5.2. Identification Strategy and Falsification Tests

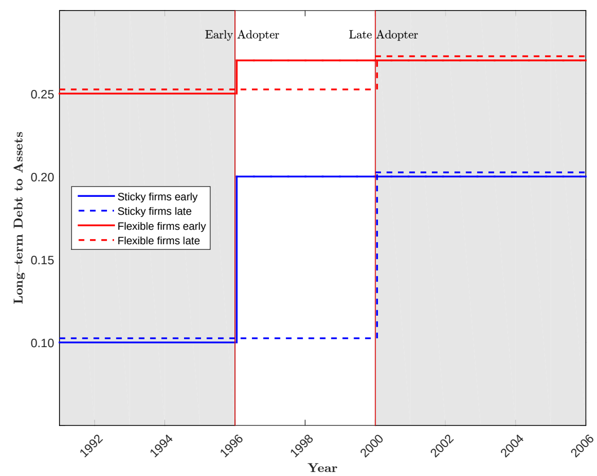
Panel A: Quadruple-differences



Panel B: Falsification Test I



Panel C: Falsification Test II



This figure describes our quadruple-differences strategy (Panel A) and two falsification tests (Panels B and C). The shaded areas represent the years whose observations we exploit in each test. All Panels report the model's predictions for the evolution of the ratio of long-term debt to assets across four groups of firms in the period 1988 to 2006. In each Panel, the two bottom lines refer to inflexible-price firms in early states that implemented the deregulation of interstate branching between 1996 and 1998 (blue, solid), and in late states that implemented the deregulation after 2000 (red, dashed). The two top lines refer to flexible-price firms in early states (black, dotted) and late states (green, dash-dot). The model predicts in each type of state, the increase in the ratio of long-term debt to assets increases more for inflexible-price firms than for flexible-price firms after the deregulation.

Table 2.5.1. Summary Statistics

This table reports descriptive statistics used in the empirical analysis for firms with non-missing price stickiness measure in Panel A and correlations across variables in Panel C. FPA measures the frequency of price adjustment. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $FPADummy$ is a dummy that equals 1 for firms in the top 25% of the distribution by the frequency of price adjustment; $Lt2A$ is long-term debt to total assets; $Prof$ is the profitability ratio, defined as operating income before depreciation to sales; $Cf2A$ is income and extraordinary items plus depreciation and amortization to total assets; $C2A$ is cash and short-term investments to total assets; $It2A$ is intangible assets to total assets; PCM is the price-to-cost margin; and HHI is the Herfindahl-Hirschman index of sales at the Fama & French 48 industry level. Stock-level data are from CRSP and financial statement data are from Compustat. The sample period is January 1982 to December 2014.

Panel A. Summary Statistics

	FPA (1)	FPA Dummy (2)	Lt2A (3)	Prof (4)	Size (5)	BM (6)	It2A (7)	PCM (8)	HHI (9)
Mean	0.14	0.25	0.21	0.15	8.25	0.60	0.26	0.37	0.11
Median	0.07	0.00	0.20	0.15	8.29	0.49	0.23	0.34	0.08
Std	0.14	0.43	0.13	0.08	1.39	0.41	0.17	0.18	0.10
Min	0.00	0.00	0.00	−0.47	4.16	0.05	0.01	0.05	0.01
Max	0.71	1.00	0.62	0.97	11.62	2.23	0.74	0.83	0.93
Nobs	9,133	9,133	9,176	9,182	9,190	9,054	9,105	9,190	9,190

Panel B. Correlations

	FPA (1)	FPA Dummy (2)	Lt2A (3)	Prof (4)	Size (5)	BM (6)	It2A (7)	PCM (8)
FPA Dummy	0.869∗∗∗							
Lt2A	0.249∗∗∗	0.200∗∗∗						
Prof	−0.144∗∗∗	−0.115∗∗∗	−0.284∗∗∗					
Size	0.128∗∗∗	0.116∗∗∗	0.121∗∗∗	−0.0649∗∗∗				
BM	0.341∗∗∗	0.274∗∗∗	0.258∗∗∗	−0.456∗∗∗	−0.0253∗			
It2A	−0.224∗∗∗	−0.187∗∗∗	0.109∗∗∗	−0.131∗∗∗	0.297∗∗∗	−0.192∗∗∗		
PCM	−0.212∗∗∗	−0.194∗∗∗	−0.167∗∗∗	0.461∗∗∗	−0.190∗∗∗	−0.383∗∗∗	0.141∗∗∗	
HHI	−0.0925∗∗∗	−0.0976∗∗∗	−0.0647∗∗∗	0.133∗∗∗	0.133∗∗∗	−0.164∗∗∗	0.136∗∗∗	0.0581∗∗∗

Table 2.5.2. Price Flexibility and Likelihood of Default

This table reports the results of logit regressions regressing future defaults on the frequency of price adjustment, FPA, and total debt. Robust standard errors are reported in parentheses. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Total Debt is the ratio of total debt to sum of liability and market capitalization. The default data are from the Moody's default database. The dependent is a dummy for having a default within years 1 to 5. The sample period is January 1980 to December 2013.

	Def_{t+1}	Def_{t+2}	Def_{t+3}	Def_{t+4}	Def_{t+5}
FPA	-2.02	-2.13*	-1.84*	-1.80**	-1.68**
	(-1.24)	(-1.81)	(-1.91)	(-2.14)	(-2.26)
Total Debt	6.89***	6.16***	5.68***	5.36***	4.93***
	(7.25)	(9.71)	(10.75)	(11.37)	(11.65)
Constant	-7.68***	-6.68***	-6.11***	-5.69***	-5.32***
	(-18.99)	(-25.17)	(-28.02)	(-30.09)	(-32.17)
Observations	13,092	13,092	13,092	13,092	13,092
Pseudo R^2	0.097	0.084	0.075	0.069	0.060

t-stats in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

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Table 2.5.3. Panel Regressions of Leverage on Price Flexibility

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA, and firm characteristics. Standard errors are clustered at the firm level. Columns (1) to (3) use the continuous measure of the frequency of price adjustment and columns (4) to (6) use a dummy which equals 1 if the firm is in the top tertile of the frequency of price adjustment distribution. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $Prof$ is operating income over total assets, $Size$ is the logarithm of sales, BM is the book-to-market ratio, $It2A$ is intangible assets to total assets, PCM is the price-to-cost margin, and HHI is the Herfindahl-Hirschman index of sales at the Fama & French 48 industry level. Stock-level data are from CRSP and financial statement data are from Compustat. The sample period is January 1982 to December 2014.

	FPA			FPA Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
FPA	0.18***	0.07**	0.09***	0.06***	0.02*	0.04**
	(4.96)	(2.33)	(3.10)	(3.93)	(1.75)	(2.41)
Prof	−0.22***	−0.24***	−0.32***	−0.20**	−0.26***	−0.29***
	(−3.02)	(−3.92)	(−5.76)	(−2.39)	(−3.78)	(−4.08)
Size	0.00	0.00	0.00	0.00	0.00	0.00
	(1.33)	(0.40)	(0.33)	(−0.11)	(−0.29)	(−0.07)
BM	0.05***	0.02**	0.02*	0.06***	0.04***	0.03***
	(5.31)	(2.27)	(1.73)	(5.46)	(4.02)	(2.81)
It2A	0.11***	0.12***	0.14***	0.14***	0.15***	0.15***
	(3.83)	(4.21)	(5.07)	(3.23)	(3.66)	(3.84)
PCM	0.00	−0.03	0.06**	0.02	0.00	0.09**
	(−0.12)	(−1.13)	(2.00)	(0.40)	(0.07)	(2.36)
HHI	−0.03	0.07	0.07	−0.03	0.08	0.09
	(−0.72)	(1.65)	(1.42)	(−0.48)	(1.27)	(1.37)
Constant	0.12***	0.22***	0.19***	0.15***	0.22***	0.18***
	(3.47)	(4.90)	(4.59)	(3.63)	(4.23)	(3.66)
Year FE1	X	X	X	X	X	X
Industry FE1		X			X	
Industry FE2			X			X
Nobs	8,824	8,824	8,824	4,408	4,408	4,408
Adjusted R^2	0.16	0.27	0.34	0.18	0.28	0.37

t-stats in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

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TABLE 2.5.4. Panel Regressions of Leverage on Price Flexibility (Errors-in-Variables)

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA, and firm characteristics. Standard errors are clustered at the firm level. Columns (1) to (3) use the continuous measure of the frequency of price adjustment and columns (4) to (6) use a dummy which equals 1 if the firm is in the top tertile of the frequency of price adjustment distribution. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $Prof$ is operating income over total assets, Size is the logarithm of sales, BM is the book-to-market ratio, It2A is intangible assets to total assets, PCM is the price-to-cost margin, and HHI is the Herfindahl-Hirschman index of sales at the Fama & French 48 industry level. Stock-level data are from CRSP and financial statement data are from Compustat. The sample period is January 1982 to December 2014.

	OLS	3rd cum	4th cum	5th cum
	(1)	(2)	(3)	(4)
FPA	0.18∗∗∗	0.26 ∗ ∗	0.21∗∗∗	0.10∗∗∗
	(4.96)	(2.23)	(4.15)	(3.67)
Prof	−0.22∗∗∗	0.18	−0.19 ∗ ∗	−0.31∗∗∗
	(−3.02)	(0.79)	(−2.41)	(−4.23)
Size	0.00	−0.02	0.01 ∗ ∗	0.02∗∗∗
	−1.33	(−1.56)	−2.06	−4.81
BM	0.05∗∗∗	0.09	0.10∗∗∗	0.09∗∗∗
	(5.31)	(1.51)	(4.76)	(7.68)
It2A	0.11∗∗∗	0.66 ∗ ∗	0.03	−0.14∗∗∗
	(3.83)	(2.56)	(0.42)	(−4.31)
PCM	0.00	−0.15∗	0.05	0.09∗∗∗
	(−0.12)	(−1.83)	(1.60)	(3.23)
HHI	−0.03	−0.12∗	0.00	0.02
	(−0.72)	(−1.66)	(0.06)	(0.45)
Constant	0.12∗∗∗	0.13∗	0.04	0.04
	(3.47)	(1.85)	(1.08)	(1.10)
Nobs		8,824		
Adjusted R^2		0.16		

t-stats in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2.5.5. Interstate Bank Branching Deregulation, Price Flexibility, and Leverage

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA; a dummy which equals 1 for years after the state where the firm operates had started to implement the interstate bank branching deregulation, Deregulated; the interaction term between FPA and the dummy, FPA × debranch; and firm characteristics. Standard errors are clustered at the firm level. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $IndustryFE1$ is a set of eight dummies that capture 1-digit SIC codes. $IndustryFE2$ is a set of forty-eight dummies that capture the Fama & French 48 industries. The sample period is January 1982 to December 2014.

	FPA			FPA Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
FPA × Deregulated	−0.15***	−0.16***	−0.16***	−0.04**	−0.04**	−0.04***
	(−4.08)	(−4.25)	(−4.64)	(−2.41)	(−2.31)	(−2.71)
FPA	0.30***	0.16***	0.17***	0.09***	0.05***	0.06***
	(8.04)	(4.84)	(5.16)	(5.77)	(3.05)	(3.58)
Deregulated	0.05***	0.02	0.03**	0.04***	0.01	0.01
	(5.75)	(1.50)	(2.15)	(3.39)	(0.86)	(0.78)
Constant	0.15***	0.20***	0.17***	0.16***	0.21***	0.18***
	(19.75)	(8.31)	(8.71)	(15.67)	(7.55)	(6.60)
Year FE		X	X		X	X
Industry FE1		X			X	
Industry FE2			X			X
Nobs	9,119	9,119	9,119	4,558	4,558	4,558
Adjusted R^2	0.08	0.20	0.27	0.09	0.19	0.30

t-stats in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2.5.6. Interstate Bank Branching Deregulation, Price Flexibility, and Leverage by External Finance Dependence

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA; a dummy which equals 1 for years after the state where the firm operates had started to implement the interstate bank branching deregulation, Deregulated; the interaction term between FPA and the dummy, FPA × debranch; and firm characteristics. Standard errors are clustered at the firm level. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $IndustryFE1$ *is a set of eight dummies that capture one-digit SIC codes.* $IndustryFE2$ *is a set of forty-eight dummies that capture the Fama & French 48 industries. The sample period is January 1982 to December 2014.*

	FPA		FPA Dummy	
	Low Cash	High Cash	Low Cash	High Cash
	(1)	(2)	(3)	(4)
FPA × Deregulated	−0.19***	−0.06	-0.06***	−0.01
	(−4.51)	(−0.92)	(-3.06)	(−0.47)
FPA	0.26***	0.14***	0.08***	0.04**
	(7.33)	(2.75)	(5.29)	(2.02)
Deregulated	0.03*	0.04**	0.02	0.04
	(1.94)	(2.16)	(0.89)	(1.42)
Constant	0.18***	0.08***	0.18***	0.11***
	(17.47)	(7.54)	(14.51)	(6.01)
Year FE	X	X	X	X
Nobs	6,075	3,044	3,151	1,407
Adjusted R^2	0.08	0.08	0.09	0.07

t-stats in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2.5.7. Interstate Bank Branching Deregulation, Price Flexibility, and Leverage: Early vs. Late Deregulating States

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA; a dummy that equals 1 for years after 1996, post1996; a dummy that equals 1 for firms in states that implemented the interstate bank branching deregulation in the first wave, between 1996 and 1998, early; and all the interactions between these variables. In the first falsification test of columns (4)-(6), a dummy that equals 1 for years after 1992, post1992, replaces post1996. In columns (1)-(3), the sample period is January 1982 to December 1999; in columns (4)-(6), it is January 1982 to December 1995; in columns (4)-(6), it is January 1982 to December 1995 and January 2001 to December 2014. Standard errors are clustered at the firm level. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Stock-level data are from CRSP and financial statement data are from Compustat.

	All (1)	Low Cash (2)	High Cash (3)	Falsification Test 1 (4)	Falsification Test 2 (5)
FPA × post1996 × early	−0.17∗∗	−0.16∗	0.21		−0.01
	(−2.00)	(−1.78)	(0.84)		(−0.09)
FPA × post1996	0.08	0.08	−0.23		−0.14∗
	(0.99)	(0.95)	(−0.95)		(−1.89)
FPA × early	0.01	0.00	−0.06	0.04	0.01
	(0.16)	(−0.02)	(−0.44)	(0.52)	(0.16)
post1996 × early	0.02	0.00	0.00		0.00
	(0.88)	(0.17)	(−0.09)		(0.12)
FPA	0.28∗∗∗	0.27∗∗∗	0.18	0.27∗∗∗	0.28∗∗∗
	(4.37)	(3.83)	(1.62)	(3.81)	(4.37)
post1996	0.02	0.02	0.02		0.05∗∗
	(0.87)	(0.89)	(0.59)		(2.40)
early	0.00	0.03	−0.02	0.00	0.00
	(0.20)	(1.24)	(−0.86)		(0.20)
FPA × post1992 × early				−0.12	
				(−1.39)	
FPA × post1992				0.06	
				(0.73)	
post1992 × early				0.02	
				(0.88)	
post1992				−0.01	
				(−0.48)	
Constant	0.15∗∗∗	0.16∗∗∗	0.11∗∗∗	0.15∗∗∗	0.15∗∗∗
	(7.27)	(6.96)	(7.07)	(6.76)	(7.27)
Nobs	5,376	3,796	1,580	4,110	7,549
Adjusted R^2	0.10	0.10	0.02	0.10	0.08

t-stats in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

CHAPTER 3

Innovation and Compensation Benchmarking

3.1. Introduction

The financial contracting view of executive compensation, dating back to Holmstrom (1979) and Holmstrom (1982), have emphasized that relative performance evaluation (RPE) constitutes an effective way of reducing moral hazard. The intuition is that if firm performances are correlated, then observing another firm's performance provides additional information concerning the underlying unobservable shock. Thus the compensation contract offered to the CEO should account for this information. By allowing the investors to benchmark the CEO's pay relative to market or industry performance, the contract reduces agency cost and improves risk-sharing among risk-averse agents.

This view of compensation contracting leads to an extensive empirical literature investigating its validity. The results so far have been mixed. Early studies such as Jensen and Murphy (1990) find that RPE is not important in managerial compensation schemes. In contrast, Gibbons and Murphy (1990), using a more direct test, show that higher value-weighted industry returns lowers the growth of CEO pays. Barro and Barro (1990) and Joh (1999) find that compensation actually increases with industry performance, opposite to what the agency cost story would predict. Betrand and Mullainathan (2001) show that factors outside the management's control, such as oil price shock, leads to higher pay. They call this "pay for luck" and argue that it is a result of poor governance. The inconclusiveness of the empirical evidence suggests that other factors may be at work that determine the agency trade-off.

In the current paper, I propose that innovativeness of the firm and industry can be lead to cross-sectional differences in executive compensation. Empirically, I show that "pay for luck" is mainly concentrated in firms that are in the most innovative quintile as measured by patent-related metrics such as patent counts. The same effect exists at the industry level. Among the most innovative industries, executives are compensated for industry performances outside of their control. For industries that do not have many patents, the "pay for luck" coefficient is statistically insignificant. This empirical regularity might result if incentivizing innovation changes the correlational structure of the firm's performance relative to the industry.

One possibility is that innovation might generate technological spillover and open new markets as competitors try to imitate. Thus the performance of the industry might provide additional information about the unobserved effort of the executives, and innovative firms reward their executives for industry-wide stock returns. Even without technological spillover, exploration usually involves much higher uncertainty and lower correlation between the firm's project and that of its rivals. In this case, a traditional principal-agent optimal contract that completely screens out the rivals' performance will also decrease the incentive of agents. I leave a detailed investigation of the mechanism driving this empirical phenomenon to future research.

My work fits into two broad strands of literature. The first strand builds upon the early empirical work on executive compensation, and tries to find sources of cross-sectional heterogeneity that affect the effectiveness of relative benchmarking. Aggarwal and Samwick (1999a) study the structure of product market competition on RPE. They find that the need to soften product market competition might induce a positive weight on rival firm performance, and firms in more competitive industries place greater weight on rival firm performance relative on own firm performance. More recently, Garvey and Milbourn (2006) show that executives are rewarded for good luck, but not penalized for bad. Gopalan et al. (2010) propose that firm structure, such as single- or multi-divisional, changes the CEO's choice set in terms of exposure to sector performance. This might lead to suboptimality of RPE. In order to generate this as part of optimal contracting, they make industry exposure a choice variable in their model. Our model is simpler and takes exposure itself as exogenous. Finally, Lewellen (2013) suggests that the lack of support for RPE results from an incorrect measurement of the peer group. I add to the literature by explicitly recognizing the importance of innovation at both the firm and the industry level in affecting the compensation structure.

The second strand of literature grows out of recent research on innovation-incentiving contracts such as Manso (2011). In related empirical work, Ederer and Manso (2013) show in a lab setting that standard pay-for-performance is ineffective in encouraging subjects to explore new business strategies. Tian and Wang (2014) study firms backed by venture capitalists (VC) and find that more tolerance for early failure in the VC investors leads to more innovative output.

3.2. Empirical Analysis

Data and Descriptive Statistics. The data come from three sources. Firm returns and volatility come from the Center for Research in Security Prices (CRSP). Similarly, industry returns and volatility are computed using firm level data from CRSP. The compensation data are drawn from S&P's ExecuComp database in Compustat. The patent data come from the NBER Patent database. Following most empirical papers, I only use executives identified as CEO of the firm. In addition, I drop any firms with fiscal year ending not in December to align the return data with industry level return, and facilitate peer group comparison. Since I am analyzing year-to-year changes in total compensation, I follow prior literature such as Garvey and Milbourn (2006) and include only observations in which the CEO has been with the firm for two full years. Another reason for this is that innovation takes time to develop and new CEOs are not likely to have influenced the most recent innovation. I also exclude financial firms with 6 as their one-digit SIC code as patents are not a good metric for their innovativeness but my results do not change if we include them. The final sample consists of 7388 frm-year observations from 1992 to 2006. The summary statistics of the full sample as well as the subsample used in regression analysis are presented in Table 3.3.1.

The full sample and subsample that I use for regression analysis are qualitatively comparable. The average stock return and volatility are 0.184 and 0.111 respectively in the full sample while they are 0.185 and 0.112 in the subsample. Our subsample tends to contain larger firms, with an average market capitalization of 7791 million while the average market capitalization in the overall sample is 6270 million. This might have led to the subsample having a slightly higher total compensation of $4628 thousand compared to the full sample average of $4488 thousand. The book-to-market ratio and log asset are similar. Finally, note that some variables such as option values and total compensation exhibit significant right skewness. Therefore I winsorize all variables of interest at the 1% level.

Table 3.3.2 shows the correlation among some of the variables. As expected, the number of patents and citations exhibits a strong positive correlation with log asset and R&D expense. Interestingly, the patents and citations also have a positive correlation of 22.5% and 15.3% with total compensation. Looking at the component of total compensation, we see that the correlations are strongest for bonus at 38.5% with patents and 24.9% for citations. This is probably due to the bonus being the most discretionary part of the compensation. Overall, the positive correlation agrees with the general belief that having more patents increases the value of the firm, and CEOs are compensated for that value added.

Empirical Specifications. I follow the literature on compensation benchmarking and estimate a two-stage regression. In the first stage, the firm return is regressed on the industry return and time dummies to create a industry-specific and a firm-specific component of return.

$$y_{it} = \beta X_s + \mu_t T + \varepsilon_{it} \tag{3.2.1}$$

where X_s is the return of the industry that firm i is in, and T is a set of time dummies in years. In estimating the equation, we exclude the firm itself in calculating the industry return. We use two-digit SIC code as our definition of industry. The predicted value giving the industry return are referred in the rest of the paper as "luck" based on the assumption that the CEO has no significant control over the return of the industry on average. The residuals giving the firm-specific return are henceforth referred to as the "skill". Thus luck λ and skill ε are given by

$$\begin{aligned} \lambda &= \hat{\beta} X_s + \hat{\mu}_t T \\ \varepsilon &= \hat{\varepsilon}_{it} \end{aligned}$$

I recognize that these variables are merely proxies for industry performance and might be imperfect. Specifically, one cannot perfectly decompose return into industry and firm-specific component and the decomposition might be biased in the sense that some industry components are also present in the firm component and vice versa. For robustness, I conduct the the exercise using both value-weighted and equal-weighted returns. The results from the first stage regression is shown in Table 3.3.3 .

After estimating the first stage regression, I run a second stage regression using the fitted values and residuals to understand the benchmarking effects. The empirical investigation comes in two main specifications. First, I sort firms into five different groups of roughly equal number of firms by their innovativeness, with group 5 being most innovative. Then I run the following regression for each group

$$\triangle CEO\ Pay = \alpha_1 \lambda + \alpha_2 \varepsilon + \gamma X_{it} + \mu_t T \tag{3.2.2}$$

The variable $\triangle CEO\ Pay$ is the log change in CEO compensation and T is the year-fixed effect. I follow Aggarwal and Samwick (1999b) in using the change in compensation as the dependent variable since the flow, rather than the overall level, is likely to be a better proxy for actions taken by the board. The variable X_{it} are firm-level controls that includes size dummy which is 1 if the market capitalization of the firm is above the 70^{th} percentile. The variable also includes tenure and age of the CEO as well as their quadratics. Perhaps most importantly, it includes the volatility of the industry and firm-specific return as in Aggarwal and Samwick (1999b) and Gopalan et al. (2010).This essentially allows for the sensitivity of pay to luck and skill to vary according riskiness, measured by the cumulative distribution function (CDF) of variance of industry return (luck) and firm-specific return (skill). Adjusting for this heterogeneity is important in order to capture the full magnitude of pay for performance. Our interest is in knowing how α_1, the luck coefficient varies across the groups.

In the second empirical implementation, I run a joint regression on all the data. The empirical specifications are

$$\triangle CEOPay = \alpha_1\lambda + \alpha_2\varepsilon + \beta_1\lambda * Innovativeness + \beta_2\varepsilon * Innovativeness + \gamma X_{it} + \mu_t T \tag{3.2.3}$$

Here, the variable $Innovativeness$ is a proxy for innovativeness of the firm. In the empirical implementation, it includes the number of patents, empirical CDF of the number of patents, the number of citations, the number of citations per patent and the empirical CDF of the number of citations per patent. As before, X_{it} is firm-level controls. The variable $\triangle CEO\ Pay$ is the log change in CEO compensation. My investigation of firm innovativeness effects controls for firm-fixed effect. For the industry innovative effects, I try two specifications. The first specification includes firm-fixed effects to control for time-invariant factors at firm level while the second specification have industry controls instead. Since I am interested in how innovativeness affects compensation strcuture, the main variable of interest is β_1.

Empirical Results. The results show that the pay-for-luck phenomenon is stronger among more innovative firms and industries.

I first investigate the impact of firm-level innovation on compensation benchmarking. I sort firms into five groups of equal sizes by the number of patents that they have applied in a given year. Table 3.3.4 shows the regression results by groups with group 1 being the least innovative and group 5 being the most innovative. The firms in group 1 essentially have zero patents.

The dependent variable is the log change in total compensation. I explore whether the sensitivity to luck, as given by the first row, is different across firms that are differentially innovative as measured by the number of patents. Examining the coefficient of pay for luck across the groups, one sees that it is only significant in the most innovative group. In other words, The pay for luck phenomenon is entirely driven by firms with the most innovative outputs. The point estimate is positive, suggesting that there is an increase in compensation growth when the industry performs well in general.

Next, I run a pooled regression interacting innovativeness with luck to investigate the incremental impact of innovativeness on compensation for luck. The dependent variable is the log change in total compensation. I include all of the controls but only report the interaction coefficients as well as luck, skill, and size. In the first column, I interact the firm-specific and industry specific component with the raw number of patents. The second column uses the empirical CDF of the number of patents as this normalization helps in the interpretation. The third column uses the raw number of citations as the innovativeness measure. The fourth column uses citations per patent, while the last column examines the empirical CDF of the number of citations per patent. The results are shown in Table 3.3.5 .

The first row can be interpreted as the pay for luck when there is minimal amount of innovativeness. For raw patent count, it is pay for luck when the firms have 0 patents. In agreement with my first result with group regressions, none of the coefficients in the first row is statistically significant. The interaction coefficient β_1 is positive for all measures of innovativeness, suggesting that the pay for luck coefficient increases as the innovativeness of the firm increases. For the interaction terms, empirical CDF of patents, citations, and empirical CDF of citations per patent also show statistical significance at the 5% level. In general, the raw measures such as patents or citations are very dispersed with a big range of values. Considering their empirical CDF provides a normalization that makes the regression results easier to interpret. Since empirical CDF ranges from 0 to 1, the coefficient gives the increase in pay for luck from the least innovative (with empirical CDF of 0) to the most innovative (with empirical CDF of 1). Take the last column for example. Our results suggest that as the firm goes from having zero citation per patent, which is at the lowest possible value of empirical CDF, to having the most citations per patent, the pay for luck coefficient will increase by 0.57.

Overall, innovative firms' compensations tend to respond more to industry movements while less innovative firms screen out the industry component of the executive pay.

I now turn to investigate how the innovativeness of the industry affects performance benchmarking. Empirically, I use industry level patent counts as a proxy for the innovativeness of the industry. Table 3.3.6 shows group regression at two-digit SIC level and Table 3.3.7 shows the same regression at the Four-Digit SIC level. Each year, I count the number of patents that the industry has produced and then divide firms into groups of equal numbers by the innovativeness of the industry that they are in. For each regression, I also control for innovativeness at the firm level by including the empirical CDF of the patent counts.

Tthe group regressions at the two-digit SIC level show that the pay for luck coefficient is only statistically significant and positive for group 5. The results suggest that among the firms in the most innovative industry, positive shock to industry specific return leads to positive increase in log compensation change. For all the other groups, the coefficients are either insignificant or negative. Interestingly, the only other statistically significant pay for luck coefficient is for the relatively less innovative group 2. The coefficient is, however, negative. For firms in these industries, there is actually evidence of benchmarking in the sense that the compensation places negative weight on industry specific returns that are outside the CEO's control.

The regression results at the four-digit SIC level align even more precisely with our hypothesis. The point estimates are monotonically increasing from least innovative to most innovative, and they are only statistically significant for the firms in the most innovative industry. For Group 1, the coefficient on firm empirical CDF of patents is dropped because all the firms in this group have 0 patents, and therefore have constant value for CDF patents.

The two-digit SIC level might be too coarse for comparison of relative performance benchmarking as there tend to be too many firms in each industry. In reality, firms usually design the compensation in a way that only a couple of other rival firms are considered. I believe that 4-Digit SIC is a more appropriate level of industry definition. Table 3.3.8 shows industry level summary statistic when we collapse the sample into industry-year observations at the 4-Digit SIC code level.

Three hundred industries are included in our sample, with 3058 industry-year observations. On average, there are 2.42 firms in each industry in each year, and about 1.15 of the firms have at least one patent. Note that the distribution is highly skewed to the right.

Finally, I conduct a pooled regression analysis, interacting the firm-specific and industry specific component with the empirical CDF of industry level patent count. The results are reported in table 3.3.9.

In the first two columns, I run the regression with firm-fixed effects, while in the last two columns we used industry-fixed effects instead and cluster standard errors at the industry level. Columns 1 and 3 only include firm level patent control, while columns 2 and 4 include firm level patent control along with firm level patent interact with pay for luck. This is to ensure that my results are not driven by firm-level innovativeness. The coefficient of interest is Luck interacted with CDF Industry Patents. The coefficient is positive for all specifications. When I do not include firm-luck interactions, the coefficient is also statistically significant. Including firm-luck interaction weakens the results; the points estimates are halved and the coefficient is no longer statistically significant.

Why innovativeness affects compensation structure? A full investigation of the mechanism linking innovativeness and compensation scheme, both at the theoretical and empirical level, is beyond the scope of the current work. Here, I will just provide a conjecture. The traditional principal-agent models of compensation contract assume that industry performance provides information about the executive's hidden effort through the firm's correlation with the industry. Benchmarking the executive's pay to the industry performance takes into account that additional information and provides an effective way to reduce moral hazard. The crucial assumption is that the correlation is fixed and outside the control of the executive.

When a firm wants to incentivize executives to engage in experimentation, both the industry performance and the industry's correlation structure with the firm are distorted. For example, there might be positive externalities associated with a firm's innovative activities. Jaffe (1986) shows that the R&D productivity of a company is increased by the R&D of companies that are in the same technological area. More recently, Matray (2016) argues that innovation by one firm fosters innovation by firms in the same geographical area, due to learning across firms and inventors moving to another employer. In both cases, the other firms in the innovative firm's industry or geographical location benefit. This means that the executives' decisions will have an impact on how related sectors of firm might perform. Thus the sector performance can provide information about the effort of the executives not just through the connection with the firm. If the executive is not rewarded for sector performance, she will have no incentive to affect sector movements, thereby decreasing the incentive to engage in innovative activities. Gopalan et al. (2010) develops a model that is closely related to this line of reasoning. They show that if the CEO has a choice over the firm's exposure to the sector, then the optimal compensation contract will reward the CEO for industry performance.

3.3. Conclusion

Many have interpreted the lack of empirical support for relative performance evaluation as failure of corporate governance and evidence of executive entrenchment. In this chapter, I use patent-based metrics as proxies for innovativeness of the firm and industry and study the relationship between innovativeness and executive compensation. I find that among more innovative firms, there is stronger evidence of pay for industry performance. Moreover, firms in more innovative industries also show stronger pay for industry performance. I conjecture that motivating innovation might require different contract design and thus different firms implement different compensation schemes. Further work can be done in providing an optimal contract model of compensation that rationalizes this empirical documentation. Finally while patent-based metrics are not perfect proxies, it is pervasive in the literature and I hope that my work will serve as a stepping stone to future empirical work studying cross-sectional differences in performance benchmarking and optimal contracting in general.

Table 3.3.1. Summary Statistics

This table reports the number of observations, mean, median, and standard deviations, as well as minimum and maximum of compensation-related variables. The top panel shows the statistics for all the firms in the ExecuComp database. The bottom panel reports the same summary statistics for just the subsample that is matched to the NBER patent database. It also reports the number of patents that the firm has for each year, and the number of citations for those patents. The final sample consists of observations from 1992 to 2006.

	count	mean	sd	min	p50	max
Full Sample						
Salary	24813	628.1577	350.0464	0	570.833	8100
Bonus	24813	649.4975	1598.311	-0.001	280.32	102015.2
Option Black-Scholes Value	21295	2167.68	8581.07	0	536.397	600347.4
Total Compensation	24568	4487.976	10377.87	0	2131.913	655448
Tenure	23763	6.792366	7.392411	0	4	56
Age	23284	55.57718	7.599458	29	56	91
Stock Return	24813	0.1836725	0.6310605	-0.9784173	0.103333	17.72632
Stock Volatility	24788	0.1109842	0.0733365	0.0015766	0.0930379	2.746621
Log Asset	24813	7.429081	1.764566	0	7.250918	14.59833
Market Capitalization	24813	6269.554	21080.52	1.937063	1313.593	511887.1
Book to Market	24813	0.5169257	0.8930577	-55.05389	0.4436252	37.49498
Our Subsample						
Salary	7388	676.6299	393.5374	0	600	5806.651
Bonus	7388	630.331	1142.944	0	293.4355	17031.25
Option Black-Scholes Value	6314	2219.185	7336.668	0	606.807	290594.8
Total Compensation	7345	4628.436	8485.865	0	2310.608	293097.3
Tenure	7144	8.235302	6.956651	2	6	54
Age	6892	56.47954	7.365178	30	57	90
Stock Return	7388	0.1854417	0.6494278	-0.9784173	0.1029241	14.94336
Stock Volatility	7384	0.1124997	0.0740406	0.0171401	0.0936784	1.074093
Log Asset	7388	7.324453	1.681371	0	7.177766	13.58652
Market Capitalization	7388	7791.074	25100.53	3.443687	1509.578	507216.6
Book to Market	7388	0.4721873	0.8411908	-31.06736	0.3985149	37.49498
Patents	7388	27.33284	147.4964	0	0	4344
Citations	7388	186.8545	1349.078	0	0	45559

Table 3.3.2. Correlation Table

This table reports the correlation among the compensation-related variables and patent measures. The sample consists of observations from 1992 to 2006.

	Salary	Bonus	Option Black-Scholes Value	Total Compensation	Tenure	R&D	Log Asset	Book to Market	Patents	Citations
Salary	1									
Bonus	0.660	1								
Option Black-Scholes Value	0.151	0.183	1							
Total Compensation	0.381	0.415	0.919	1						
Tenure	-0.0576	-0.0421	-0.0396	-0.0575	1					
R&D	0.437	0.361	0.131	0.232	-0.100	1				
Log Asset	0.760	0.552	0.173	0.345	-0.132	0.493	1			
Book to Market	-0.0262	-0.0976	-0.0560	-0.0672	0.0390	-0.0425	-0.0220	1		
Patents	0.331	0.385	0.143	0.225	-0.0319	0.502	0.358	-0.0408	1	
Citations	0.215	0.249	0.104	0.153	-0.0226	0.379	0.266	-0.0280	0.802	1

Table 3.3.3. First Stage Regression Table

This table reports the regression of a firm's return on its industry return. Industry is defined at the two-digit SIC code level. In calculating industry return, the firm itself is excluded. In column 1, the firms in the industry is value-weighted while in column 2, the returns are equal-weighted. The sample consists of observations from 1992 to 2006.

	Value Weighted	Equal Weighted
Value Weighted Industry Return	0.861***	
	(23.27)	
Equal Weighted Industry Return		0.818***
		(24.76)
Constant	0.0925*	-0.0145
	(1.87)	(-0.29)
Observations	7388	7388
Adjusted R^2	0.128	0.136

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.4. Regression by Quintiles Using Log Change Compensation as Dependent

This table reports the regression of the log change of CEO's compensation on skill, luck, and various controls by quintiles of innovativeness as measured by patent counts. Luck is the industry component of firm performance estimated via a regression of firm return on industry return. Skill is firm-specific component of return, estimated as the residual of the regression of firm return on industry return. CDF Luck Variance is the empirical cumulative distribution function of the industry specific component of stock return. CDF Skill Variane is the empirical cumulative distributive function of the firm specific component of stock return. The sample consists of observations from 1992 to 2006.

	Group 1	Group 2	Group 3	Group 4	Group 5
Luck	0.360	-0.638	-0.371	-0.0412	0.726**
	(1.08)	(-0.88)	(-0.85)	(-0.11)	(2.53)
Skill	0.500***	0.229	0.141	0.621***	0.140
	(2.84)	(1.33)	(0.67)	(3.52)	(0.93)
Size	0.0276	0.129	0.140	-0.0106	-0.0155
	(0.22)	(0.84)	(0.84)	(-0.09)	(-0.11)
CDF Luck Variance	0.293*	-0.0300	0.0359	-0.0504	0.00152
	(1.81)	(-0.14)	(0.23)	(-0.33)	(0.01)
CDF Skill Variance	0.0674	-0.163	-0.274	-0.122	-0.0800
	(0.44)	(-1.01)	(-1.62)	(-0.93)	(-0.65)
Luck w.CDF Luck Variance	-0.577	1.119	0.622	0.219	-0.655
	(-1.30)	(1.46)	(1.07)	(0.49)	(-1.50)
Skill w.CDF Skill Variance	-0.391*	-0.0908	0.286	-0.541**	0.0984
	(-1.65)	(-0.38)	(1.11)	(-2.26)	(0.47)
Tenure	-0.00611	0.0149	-0.000395	-0.000255	-0.0139
	(-0.37)	(0.65)	(-0.02)	(-0.02)	(-0.84)
Tenure2	0.0000206	-0.000170	-0.00000589	-0.000266	0.000426
	(0.04)	(-0.28)	(-0.01)	(-0.82)	(0.63)
Age	0.115**	0.00547	-0.0663	0.0535	0.0542
	(2.09)	(0.09)	(-0.52)	(1.03)	(0.86)
Age2	-0.000939**	-0.000162	0.000607	-0.000526	-0.000481
	(-2.04)	(-0.32)	(0.49)	(-1.16)	(-0.88)
Constant	-3.696**	0.328	2.041	-1.035	-1.562
	(-2.24)	(0.18)	(0.60)	(-0.70)	(-0.87)
Observations	1291	1262	1286	1291	1312
Adjusted R^2	0.037	0.019	0.128	0.048	0.050

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.5. Log Change in Total Compensation

This table reports the regression of the log change of CEO's compensation on skill, luck, and various controls and interactions. Luck is the industry component of firm performance estimated via a regression of firm return on industry return. Skill is firm-specific component of return, estimated as the residual of the regression of firm return on industry return. CDF Luck Variance is the empirical cumulative distribution function of the industry specific component of stock return. CDF Skill Variane is the empirical cumulative distributive function of the firm specific component of stock return. The sample consists of observations from 1992 to 2006.

	Patent	CDF Patents	Citations	Citations/Patent	CDF Citations/Patent
Luck	0.120	-0.311	0.119	0.122	-0.209
	(0.65)	(-1.04)	(0.65)	(0.64)	(-0.70)
Skill	0.416***	0.440***	0.396***	0.397***	0.445***
	(5.03)	(3.60)	(4.84)	(5.18)	(3.67)
Size	-0.0121	-0.0169	-0.0145	-0.0139	-0.0116
	(-0.26)	(-0.36)	(-0.31)	(-0.29)	(-0.25)
Luck w. Patents	0.00112*				
	(1.68)				
Skill w. Patents	-0.000446				
	(-0.97)				
Luck w. CDF Patents		0.722**			
		(2.53)			
Skill w. CDF Patents		-0.0581			
		(-0.49)			
Luck w. Citations			0.000173**		
			(2.08)		
Skill w. Citations			-0.00000653		
			(-0.10)		
Luck w. Citations per Patent				0.0108	
				(0.86)	
Skill w. Citations per Patent				-0.000586	
				(-0.18)	
Luck w. CDF Citations per Patent					0.570**
					(1.96)
Skill w. CDF Citations per Patent					-0.0792
					(-0.71)
Constant	-0.462	-0.438	-0.386	-0.417	-0.334
	(-0.98)	(-0.92)	(-0.82)	(-0.89)	(-0.70)
Observations	6442	6442	6442	6442	6442
Adjusted R^2	0.044	0.045	0.043	0.043	0.044

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.6. Regression by Two-Digit Industry Groups

This table reports the regression of the log change of CEO's compensation on skill, luck, and various controls by quintiles of industry innovativeness as measured by patent counts. Industry is defined at the two-digit SIC code level. Luck is the industry component of firm performance estimated via a regression of firm return on industry return. Skill is firm-specific component of return, estimated as the residual of the regression of firm return on industry return. CDF Luck Variance is the empirical cumulative distribution function of the industry specific component of stock return. CDF Skill Variane is the empirical cumulative distributive function of the firm specific component of stock return. The sample consists of observations from 1992 to 2006.

	Group 1	Group 2	Group 3	Group 4	Group 5
Luck	0.248	-0.702**	-0.562	0.339	0.692**
	(0.60)	(-2.21)	(-1.01)	(0.59)	(2.15)
Skill	0.654**	0.671***	0.260	0.194	0.296**
	(2.40)	(4.20)	(1.25)	(1.12)	(2.09)
Size	0.182	0.00888	-0.0780	0.124	-0.103
	(1.45)	(0.06)	(-0.60)	(0.87)	(-0.67)
CDF Luck Variance	0.376**	-0.148	-0.0707	0.0885	-0.134
	(2.00)	(-1.20)	(-0.43)	(0.43)	(-0.77)
CDF Skill Variance	-0.211	-0.132	-0.0940	-0.280*	0.182
	(-1.55)	(-0.95)	(-0.54)	(-1.72)	(1.43)
Luck w.CDF Luck Variance	0.0228	0.631*	0.899	-0.730	-0.686
	(0.05)	(1.90)	(1.34)	(-1.04)	(-1.58)
Skill w.CDF Skill Variance	-0.556	-0.534**	-0.0442	0.00318	-0.101
	(-1.61)	(-2.57)	(-0.17)	(0.01)	(-0.56)
CDF Patents	0.0406	0.131	0.276	0.274	0.0740
	(0.03)	(0.31)	(0.56)	(0.74)	(0.19)
Constant	-3.442	-2.633	5.749	0.0246	-0.771
	(-1.53)	(-1.36)	(1.54)	(0.01)	(-0.48)
Observations	1279	1291	1278	1272	1322
Adjusted R^2	0.063	0.077	0.051	0.033	0.069

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.7. Regression by Four-Digit Industry Groups

This table reports the regression of the log change of CEO's compensation on skill, luck, and various controls by quintiles of industry innovativeness as measured by patent counts. Industry is defined at the two-digit SIC code level. Luck is the industry component of firm performance estimated via a regression of firm return on industry return. Skill is firm-specific component of return, estimated as the residual of the regression of firm return on industry return. CDF Luck Variance is the empirical cumulative distribution function of the industry specific component of stock return. CDF Skill Variane is the empirical cumulative distributive function of the firm specific component of stock return. The sample consists of observations from 1992 to 2006.

	Group 1	Group 2	Group 3	Group 4	Group 5
Luck	-1.746	-0.225	0.405	0.515	0.722***
	(-1.63)	(-0.50)	(1.39)	(1.24)	(2.63)
Skill	0.374	0.384***	0.604***	0.313	0.205
	(1.22)	(2.70)	(3.64)	(1.48)	(1.41)
Size	0.0583	-0.0529	-0.0634	-0.115	0.0733
	(0.46)	(-0.42)	(-0.60)	(-0.72)	(0.63)
CDF Luck Variance	-0.311	0.00763	0.0168	0.157	-0.0807
	(-1.27)	(0.04)	(0.15)	(0.94)	(-0.53)
CDF Skill Variance	-0.0485	-0.138	0.00155	-0.161	0.0856
	(-0.29)	(-0.88)	(0.01)	(-1.29)	(0.64)
Luck w.CDF Luck Variance	2.252**	0.453	-0.379	-0.622	-0.380
	(1.97)	(0.80)	(-1.03)	(-1.37)	(-0.90)
Skill w.CDF Skill Variance	-0.175	-0.0906	-0.546**	-0.116	0.00873
	(-0.45)	(-0.49)	(-2.42)	(-0.40)	(0.05)
CDF Patents		1.409*	-0.179	0.424	-0.0612
		(1.70)	(-0.59)	(0.86)	(-0.17)
Constant	-0.505	0.447	-0.681	-0.277	-0.755
	(-0.29)	(0.18)	(-0.45)	(-0.13)	(-0.53)
Observations	1260	1292	1307	1291	1292
Adjusted R^2	0.050	0.054	0.044	0.058	0.068

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3.3.8. Industry Summary Statistics

This table reports the number of observations, mean, median, standard deviations, as well as minimum and maximum of industry-level patent variables. Each observation is at the industry-year level. Number of firms is the number of firms in the industry at a particular year. Number of firms w. Patents is the number of firms with at least 1 patent. Patents and citations are the total number of patents and citations on those patents at industry level in the particular year. The sample consists of observations from 1992 to 2006.

	count	mean	sd	min	p50	max
Number of Firms	3058	2.415958	2.769223	1	1	30
Number of Firms w. Patents	3058	1.152387	1.954252	0	1	22
Patents	3058	51.01177	180.398	0	1	2749
Citations	3058	303.8725	1282.898	0	0	20271
Citations per Patent	3058	2.876737	6.230962	0	0	108

Table 3.3.9. Four-Digit Industry Regression Using Log Change Compensation as Dependent

This table reports the regression of the log change of CEO's compensation on skill, luck at both firm and industry level, as well as various controls and interactions. Luck is the industry component of firm performance estimated via a regression of firm return on industry return. Skill is firm-specific component of return, estimated as the residual of the regression of firm return on industry return. CDF Luck Variance is the empirical cumulative distribution function of the industry specific component of stock return. CDF Skill Variane is the empirical cumulative distributive function of the firm specific component of stock return. CDF Industry patents is the empirical cumulative distribution of number of patents at industry level. First two columns have firm-fixed effects while the last two use industry-fixed effects.

	No Firm-Luck Interaction	Firm-Luck Interaction	No Firm-Luck Interaction	Firm-Luck Interaction
Luck	-0.198	-0.407	-0.165	-0.319
	(-0.68)	(-1.22)	(-0.71)	(-1.22)
Skill	0.377***	0.380***	0.357***	0.359***
	(4.00)	(4.02)	(4.63)	(4.65)
Size	-0.0144	-0.0167	-0.00893	-0.00961
	(-0.30)	(-0.35)	(-0.30)	(-0.33)
CDF Luck Variance	0.0361	0.0326	0.0174	0.0147
	(0.62)	(0.55)	(0.32)	(0.27)
CDF Skill Variance	-0.0443	-0.0447	-0.0303	-0.0302
	(-0.89)	(-0.90)	(-0.66)	(-0.66)
Luck w.CDF Luck Variance	0.0454	0.0601	0.0601	0.0717
	(0.21)	(0.27)	(0.33)	(0.39)
Skill w.CDF Skill Variance	-0.203*	-0.206*	-0.182**	-0.184**
	(-1.90)	(-1.93)	(-1.99)	(-2.01)
CDF Patents	0.0524	-0.0542	0.0703	-0.00637
	(0.48)	(-0.45)	(0.81)	(-0.06)
Age	0.0198	0.0208	0.0107	0.0109
	(1.23)	(1.29)	(0.55)	(0.57)
Age2	-0.000203	-0.000211	-0.000117	-0.000118
	(-1.48)	(-1.54)	(-0.68)	(-0.69)
Tenure	-0.00559	-0.00585	-0.00442	-0.00454
	(-1.31)	(-1.38)	(-1.11)	(-1.14)
Tenure2	0.000154	0.000159	0.000134	0.000138
	(1.38)	(1.43)	(1.88)	(1.10)
Luck w. CDF Industry Patents	0.557**	0.320	0.487*	0.325
	(2.03)	(1.14)	(2.09)	(1.88)
CDF Industry Patents	-0.0193	0.0243	0.00875	0.0399
	(-0.19)	(0.24)	(0.08)	(0.34)
Skill w. CDF Industry Patents	0.0216	0.0276	0.0192	0.0227
	(0.23)	(0.29)	(0.23)	(0.27)
Luck w. CDF Patents		0.558**		0.398
		(1.97)		(1.46)
Constant	-0.407	-0.396	-0.266	-0.229
	(-0.86)	(-0.83)	(-0.46)	(-0.40)
Observations	6442	6442	6428	6428
Adjusted R^2	0.044	0.045	0.014	0.015
Firm-Fixed	Yes	Yes	No	No
Industry-Fixed	No	No	Yes	Yes

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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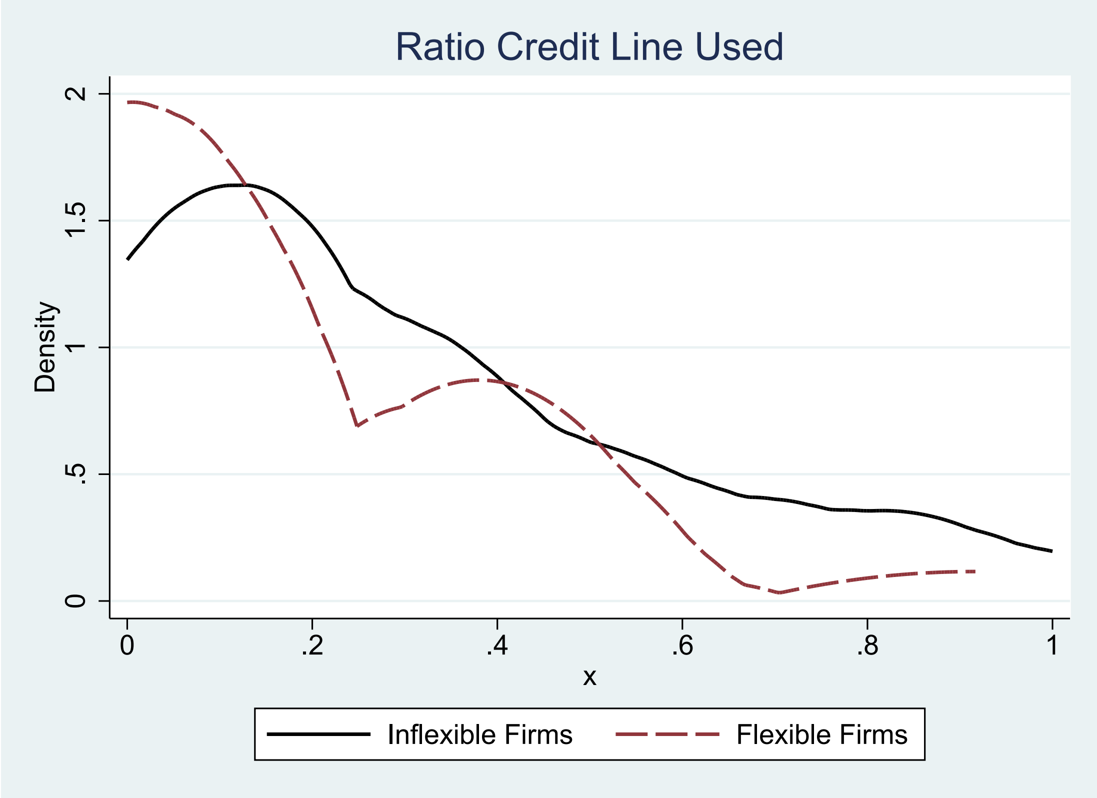
APPENDIX A

Additional Figures and Tables for Chapter 2

Figure A.1. Intensive Margin of Bank Credit Lines



This figure plots the density of the share of existing credit lines used by the firms in our sample which also belong to the random sample for which Sufi (2009) collects detailed information on the characteristics of credit lines over time. The solid black is the density for inflexible-price firms. The dashed red line is the density for flexible-price firms. Inflexible-price firms are firms in the bottom 25th percentile of the distribution by price flexibility. Flexible-price firms are firms in the top 25th percentile of the distribution by price flexibility. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. Sample period is January 1980 to December 2013.

Table A.1. Interstate Bank Branching Deregulation, Price Flexibility, and Leverage - Excluding Utilities and Financials

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA; a dummy which equals 1 for years after the state where the firm operates had started to implement the interstate bank branching deregulation, Deregulated; the interaction term between FPA and the dummy, FPA × Deregulated; and firm characteristics. Standard errors are clustered at the firm level. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $IndustryFE1$ *is a set of eight dummies that capture one-digit SIC codes.* $IndustryFE2$ *is a set of forty-eight dummies that capture the Fama & French 48 industries. The sample period is January 1982 to December 2014.*

	FPA			FPA Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
FPA × Deregulated	−0.15***	−0.15***	−0.15***	−0.04*	−0.04*	−0.04*
	(−3.33)	(−3.44)	(−3.62)	(−1.86)	(−1.75)	(−1.86)
FPA	0.24***	0.20***	0.22***	0.07***	0.05***	0.06***
	(5.89)	(5.07)	(5.26)	(3.86)	(2.96)	(3.52)
Deregulated	0.05***	0.02	0.02	0.04***	0.01	0.00
	(5.92)	(1.02)	(1.57)	(3.23)	(0.44)	(0.17)
Constant	0.15***	0.17***	0.15***	0.16***	0.20***	0.17***
	(19.22)	(7.23)	(7.67)	(16.21)	(6.95)	(6.09)
Year FE		X	X		X	X
Industry FE1		X			X	
Industry FE2			X			X
Observations	7,644	7,644	7,644	3,693	3,693	3,693
Adjusted R^2	0.06	0.09	0.18	0.05	0.11	0.23

t-stats in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.2. Panel Regressions of Leverage on Price Flexibility (by Industry)

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA; a dummy which equals 1 for years after the state where the firm operates had started to implement the interstate bank branching deregulation, Deregulated; the interaction term between FPA and the dummy, FPA × Deregulated; and firm characteristics. Standard errors are clustered at the firm level. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $IndustryFE1$ is a set of eight dummies that capture one-digit SIC codes. The sample period is January 1982 to December 2014.

	Mining (1)	Food (2)	Materials (3)	Utilities (4)	Trade (5)	Services (6)
FPA × Deregulated	−0.31∗∗	−0.24∗∗∗	0.04	−0.04	−0.21	−0.93∗∗
	(−2.68)	(−3.51)	(0.42)	(−0.42)	(−0.87)	(−2.37)
FPA	0.42∗∗∗	0.23∗∗∗	0.04	−0.12∗	0.54	0.75∗
	(3.71)	(4.47)	(0.73)	(−2.00)	(1.60)	(1.94)
Deregulated	0.05	0.041∗	0.00	0.04	0.02	0.17∗∗∗
	(0.61)	(1.91)	(−0.05)	(1.36)	(0.27)	(4.17)
Constant	0.15∗∗∗	0.17∗∗∗	0.16∗∗∗	0.34∗∗∗	0.16∗∗∗	0.11∗∗∗
	(3.11)	(11.81)	(10.07)	(24.01)	(2.84)	(4.02)
Nobs	405	3,017	3,683	1,275	423	116
Adjusted R^2	0.16	0.08	0.03	0.07	0.14	0.36

t-stats in parentheses

$*p < 0.10, **p < 0.05, ***p < 0.01$

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Table A.3. Panel Regressions of Leverage on Price Flexibility (Total Debt)

This table reports the results of regressing total debt to total assets on the frequency of price adjustment, FPA, and firm characteristics. Standard errors are clustered at the firm level. Columns (1) to (3) use the continuous measure of the frequency of price adjustment and columns (4) to (6) use a dummy which equals 1 if the firm is in the top tertile of the frequency of price adjustment distribution. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $Prof$ is operating income over total assets, $Cf2A$ is income and extraordinary items plus depreciation and amortization to total assets, $C2A$ is cash and short-term investments to total assets, $It2A$ is intangible assets to total assets, $Size$ is log of sales, BM is the book-to-market ratio, PCM is the price-to-cost margin, and HHI is the Herfindahl-Hirschman index of sales at the Fama & French 48 industry level. Stock-level data are from CRSP and financial statement data are from Compustat. The sample period is January 1982 to December 2014.

	FPA			FPA Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
FPA	0.10∗∗∗	0.03	0.09∗∗∗	0.04 ∗∗	0.01	0.03∗
	(2.69)	(0.80)	(2.69)	(2.46)	(0.78)	(1.84)
Prof	−0.27∗∗∗	−0.35∗∗∗	−0.42∗∗∗	−0.22 ∗∗	−0.32∗∗∗	−0.35∗∗∗
	(−3.33)	(−4.68)	(−5.86)	(−2.41)	(−3.86)	(−4.02)
Size	0.01∗∗∗	0.02∗∗∗	0.02∗∗∗	0.00	0.01	0.01
	(3.08)	(3.22)	(3.68)	(0.84)	(1.45)	(1.61)
BM	0.05∗∗∗	0.01	0.00	0.06∗∗∗	0.04∗∗∗	0.02∗
	(4.52)	(0.64)	(0.08)	(4.72)	(2.84)	(1.80)
It2A	0.04	0.09∗∗∗	0.11∗∗∗	0.11 ∗∗	0.15∗∗∗	0.14∗∗∗
	(1.29)	(2.65)	(3.23)	(2.23)	(3.07)	(3.30)
PCM	0.02	0.01	0.11∗∗∗	−0.02	0.00	0.09 ∗∗
	(0.57)	(0.44)	(3.08)	(−0.39)	(0.06)	(2.07)
HHI	0.02	0.12 ∗∗	0.14 ∗∗	0.05	0.18∗	0.17∗
	(0.28)	(2.06)	(2.20)	(0.61)	(1.90)	(1.84)
Constant	0.12∗∗∗	0.16∗∗∗	0.16∗∗∗	0.18∗∗∗	0.18∗∗∗	0.21∗∗∗
	(3.02)	(2.93)	(2.96)	(3.60)	(2.71)	(3.39)
Year FE1	X	X	X	X	X	X
Industry FE1		X			X	
Industry FE2			X			X
Nobs	8,838	8,838	8,838	4,413	4,413	4,413
Adjusted R^2	0.10	0.20	0.30	0.13	0.22	0.35

t-stats in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.4. Interstate Bank Branching Deregulation, Price Flexibility, and Leverage (Total Debt)

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA; a dummy which equals 1 for years after the state where the firm operates had started to implement the interstate bank branching deregulation, Deregulated; the interaction term between FPA and the dummy, FPA × debranch; and firm characteristics. Standard errors are clustered at the firm level. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $IndustryFE1$ is a set of eight dummies that capture 1-digit SIC codes. $IndustryFE2$ is a set of forty-eight dummies that capture the Fama & French 48 industries. The sample period is January 1982 to December 2014.

	FPA			FPA Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
FPA × Deregulated	−0.09∗∗	−0.09∗∗	−0.11∗∗∗	−0.03	−0.03	−0.04∗
	(−2.16)	(−2.14)	(−2.64)	(−1.50)	(−1.35)	(−1.91)
FPA	0.22∗∗∗	0.11∗∗∗	0.15∗∗∗	0.07∗∗∗	0.04∗∗	0.05∗∗∗
	(5.38)	(2.61)	(3.66)	(4.33)	(2.00)	(2.74)
Deregulated	0.02	0.01	0.02	0.02	0.00	0.00
	(1.52)	(0.77)	(1.61)	(1.09)	(−0.15)	(−0.03)
Constant	0.24∗∗∗	0.25∗∗∗	0.28∗∗∗	0.24∗∗∗	0.25∗∗∗	0.28∗∗∗
	(26.49)	(9.71)	(9.33)	(20.47)	(8.12)	(7.76)
Year FE		X	X		X	X
Industry FE1		X			X	
Industry FE2			X			X
Nobs	9,133	9,133	9,133	4,563	4,563	4,563
Adjusted R^2	0.03	0.11	0.22	0.05	0.12	0.28

t-stats in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.5. Interstate Bank Branching Deregulation, Price Flexibility, and Leverage: Early vs. Late Deregulating States (Total Debt)

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA; a dummy that equals 1 for years after 1996, post1996; a dummy that equals 1 for firms in states that implemented the interstate bank branching deregulation in the first wave, between 1996 and 1998, early; and all the interactions between these variables. Standard errors are clustered at the firm level. Columns (1) to (3) use the continuous measure of the frequency of price adjustment and columns (4) to (6) use a dummy which equals 1 if the firm is in the top tertile of the frequency of price adjustment distribution. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. The sample period is January 1982 to December 2014.

	FPA			FPA Dummy		
	All	Low Cash	High Cash	All	Low Cash	High Cash
	(1)	(2)	(3)	(4)	(5)	(6)
FPA × post1996 × early	−0.13	−0.15*	−0.11	−0.05	−0.08 **	−0.06*
	(−1.42)	(−1.74)	(−1.24)	(−1.48)	(−2.12)	(−1.83)
FPA × post1996	0.10	0.13	0.09	0.04	0.07 **	0.06 **
	(1.25)	(1.60)	(1.13)	(1.32)	(2.02)	(2.09)
FPA × early	−0.05	−0.12	−0.13*	−0.01	0.01	−0.02
	(−0.53)	(−1.35)	(−1.71)	(−0.33)	(0.20)	(−0.62)
post1996 × early	0.00	0.00	−0.01	0.00	0.03	0.02
	(−0.05)	(0.20)	(−0.27)	(−0.24)	(1.07)	(0.99)
FPA	0.25***	0.20 **	0.22***	0.08 **	0.03	0.05*
	(3.53)	(2.47)	(3.24)	(2.31)	(1.14)	(1.70)
post1996	0.01	0.00	0.02	0.01	−0.02	−0.01
	(0.51)	(0.17)	(1.07)	(0.72)	(−0.80)	(−0.68)
early	0.03	0.05 **	0.04 **	0.03	0.00	0.00
	(1.34)	(2.05)	(2.00)	(0.84)	(0.43)	(−0.11)
Constant	0.21***	0.22***	0.21***	0.22***	0.25***	0.255***
	(9.97)	(10.89)	(11.72)	(7.70)	(20.94)	(10.57)
Nobs	5,383	5,383	5,383	2,782	2,782	2,782
Adjusted R^2	0.04	0.11	0.20	0.06	0.10	0.28

t-stats in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.6. Interstate Bank Branching Deregulation, Price Flexibility, and Leverage (all Firms)

This table reports the results of regressing long-term debt to total assets on the frequency of price adjustment, FPA; a dummy which equals 1 for years after the state where the firm operates had started to implement the interstate bank branching deregulation, Deregulated; the interaction term between FPA and the dummy, FPA × debranch; and firm characteristics. Standard errors are clustered at the firm level. Equally weighted probabilities of price adjustments are calculated at the firm level using the micro-data underlying the Producer Price Index constructed by the Bureau of Labor Statistics. $IndustryFE1$ *is a set of eight dummies that capture 1-digit SIC codes.* $IndustryFE2$ *is a set of forty-eight dummies that capture the Fama & French 48 industries. The sample period is January 1982 to December 2014.*

	FPA Dummy2		
	(1)	(2)	(3)
FPA × Deregulated	−0.04***	−0.04***	−0.04***
	(−2.62)	(−2.77)	(−3.06)
FPA	0.08***	0.04***	0.04***
	(5.70)	(3.17)	(3.33)
Deregulated	0.04***	0.01	0.01
	(5.03)	(0.69)	(1.13)
Constant	0.18***	0.22***	0.18***
	(24.37)	(9.30)	(9.41)
Year FE		X	X
Industry FE1		X	
Industry FE2			X
Nobs	9,119	9,119	9,119
Adjusted R^2	0.05	0.19	0.27

t-stats in parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

APPENDIX B

Variable Definitions for Chapter 3

The variables used in the empirical analysis are as follows:

- Salary is the CEO's annual salary in thousands
- Bonus is the CEO's annual bonus in thousands
- Option Black-Scholes Value is the Black-Scholes value of the options granted to the CEO in thousands
- Total Compensation is the sum of salary, bonus, value of restricted stock grant, value of stock options granted, long-term incentive payouts, and other cash payouts
- Tenure is the difference between current fiscal year and the year the person became CEO. Since the BECAMECEO only list the first or last time the person became CEO, I supplement it by counting the number of times the CEO appear in the data.
- Age is CEO age
- Stock Return is annualized return over its fiscal year
- Stock Volatility is the annual stock return variance calculated from monthly stock return
- Log Asset is the natural logarithm of book asset
- Market Capitalization is the firm's equity value at the end of the fiscal year
- Book to Market is the ratio of book value of equity to market value of equity
- Patents is the number of patent applications that the firm filed in the data year
- Citations is the number of citations that the patents have
- Size is a dummy is that 1 if the firm is in the top 30% by market capitalization
- Luck is the industry component of firm performance estimated via a regression of firm return on industry return
- Skill is firm-specific component of return, estimated as the residual of the regression of firm return on industry return
- CDF Luck Variance is the empirical cumulative distribution function of the industry specific component of stock return
- CDF Skill Variance is the empirical cumulative distribution function of the firm specific component of stock return