Essays in Macroeconomics and Financial Economics

by

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Abstract

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This dissertation is comprised of two chapters on separate topics at the intersection of Macroeconomics and Financial Economics. The first chapter analyzes the relationship between non-financial U.S. corporations' debt structure and their behavior in the product market. The second chapter, which is co-authored with Ganesh Viswanath Natraj, examines the international real effects of monetary policy through financial markets.

In the first chapter, I answer the following crucial question: how does a non-financial firm's product market behavior interact with its capital structure choice and cash-flow process? A significant portion of the corporate finance literature considers debt borrowing the primary source of financing through which firms smooth cash-flow shocks, with bank loans and market debt the two primary sources of debt financing. However, firms can also smooth cash-flow shocks through adjustments in their variable markup of products. This behavior is consistently unaccounted for, yet provides financial flexibility, more so for firms with a loyal customer base. I study how firms smooth cash-flows via traditional financing in the form of a bank loan or market debt instrument, as well as through non-traditional internal financing generated from variable markup adjustments. First, I hypothesize the empirical relationship between a firm's markup strategy and debt financing choice, measured as the share of market debt in total debt, is conditionally non-linear. I find a robust, conditional hump-shaped relationship between the variable markup and market debt share. On average, markups rise with market debt shares, peaking at a share of 61-67% before declining. Second, I demonstrate this novel finding with a quantitative model of firm dynamics in a monopolistically competitive economy. In my model, firms set variable markups in a customer market while trading off restructurable bank loans for marginally cheaper, non-restructurable market debt. Market debt contracts reduce flexibility in cash flows, increasing a firm's incentive to raise today's profits by setting a higher markup. However, the trade-off between current and future profits implies the benefits of a high markup are maximized at a given market debt share. Beyond this share, markup reductions are required to attract new customers, thus generating the hump shape. My model replicates the empirical hump shape while matching several key cross-sectional and aggregate features of the data. Third, I use my model as a

laboratory to study the response of firms to a bank credit crunch, akin to that of the 2008-09 U.S. financial crisis. I show how my model explains 75% of the decline in total sales by public U.S. corporations following the crisis.

In the second chapter, I document the international real spillovers of major central banks policies' through their indirect effect on a set of base asset prices, by using high-frequency identification of monetary policy announcements. I implement a gross domestic product (GDP)-tracking approach to identify real spillovers of monetary policy, by mimicking real GDP news based on my set of asset returns around monetary announcements. This procedure enables me to estimate news regarding real GDP growth due to monetary policy. Most importantly, this provides me with a direction of causation from monetary announcements to real variables through their indirect effects on asset prices. In response to positive, domestic monetary shocks, I find real GDP-tracking news becomes negative for the U.S., Australia, and Canada. My methodology indicates significant spillovers of U.S. monetary policy to asset prices in periphery countries, such as Australia and Canada, with a U.S. monetary contraction leading to a significant effect in both of these countries' real GDP-tracking news measures, albeit the effects differ between both countries: contractionary U.S. monetary policy is contractionary in Australia after a year, but expansionary in Canada within two quarters.

Summarizing, my dissertation's first chapter yields crucial information for better predicting a non-financial firm's default choice. Moreover, it provides insight into how a firm's customer base – a source of market power – directly impacts capital structure decisions and vice versa. My second chapter shows the U.S. Federal Reserve is a fundamental driver of global asset prices and real output abroad, which is a topic at the core of recent policy discussions in international macroeconomics and finance.

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Chapter 1

Variable Markup Implications of Corporate Debt Structure

1.1 Introduction

In the years leading up to the 2008-09 financial crisis, most public, non-financial U.S. firms' shares of corporate market debt in total debt financing decreased rapidly due to cheap bank credit.[1] Following the 2008 collapse of investment bank Lehman Brothers, bank lending conditions tightened until late 2010 (Ivashina and Scharfstein, 2010). Consequently, market debt shares moved in the opposite direction, as most firms were forced to reduce their reliance on bank loans and increase issuances of market debt securities (Becker and Ivashina, 2014; Adrian et al., 2013).[2] For example, McDonald's and PepsiCo, two of America's largest public corporations, increased their market debt shares at the end of 2007 from 34.8% and 60.4%, to 63.3% and 80% by the end of 2010, respectively. In shifting from bank loans towards market debt, both firms, which operate in customer-based markets, differed in their ability to generate profits over their production costs. While McDonald's ratio of sales over the cost of goods sold (COGS) increased from 1.69 to 1.83, PepsiCo's decreased from 2.43 to 2.37.[3]

Considering why the primary reason a firm issues debt is to finance its product market strategy, a major contribution of this chapter is to show corporate debt structure is directly related to a firm's variable markup (sales over COGS). In the cross-section, how does the economic relationship between a firm's reliance on market debt financing and its

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[1]Rauh and Sufi (2010) study a sample of public U.S. rated firms, and show that approximately 70% of firms since 1996 hold at least two different types of debt instruments on their balance-sheets. Bank loans and corporate debt (notes, bonds, and commercial paper) compose the majority of debt used by these firms. Most recently, a report by S&P Global found corporate debt among public U.S. corporations was record $6.3 trillion as of June 2018. (Source: June 27, 2018, "Debt for US corporations tops $6 trillion," CNBC).

[2]Adrian et al. (2013) document that during the U.S. economic downturn from 2007 to 2009, total amount of new bank loan issuances *decreased* by 75%, while new bond issuances *increased* by almost 125%.

[3]A detailed breakdown of both McDonald's and PepsiCo's debt structure and accounting information is sourced from S&P's Capital IQ and Compustat Fundamentals databases.

variable markup manifest itself? More specifically, is this relationship linear or non-linear, and what is its economic significance? McDonald's and PepsiCo both increased their reliance on market debt around the time of the financial crisis, yet their variable markups moved in opposite directions. This alludes to the potential existence of a non-linear relationship between markups and market debt shares.

To answer these questions, I analyze the cross-sectional relationship between variable markups and corporate debt structure through the lens of the literature on capital structure and product market competition. Theoretically, firms with limited liability and operating in environments with competitive interactions, have an incentive to pursue riskier output strategies, and to cut markups as they accumulate debt (Brander and Lewis, 1986; Maksimovic, 1988; Lyandres, 2006). If firms also operate in a customer market, variable markups act as a strategic investment in future customers, whereby firms balance the trade-off between current and future profits (Phelps and Winter, 1970; Rotemberg and Woodford, 1993).[4] However, when a firm's financial condition is relatively fragile, it foregoes future customer base by raising its markup, in order to both increase cash flow today as well as service its debt liabilities (Chevalier, 1995a; Chevalier, 1995b; Chevalier and Scharfstein, 1996).

Building on this research, I study the relationship between debt structure and markup behaviors by analyzing two channels through which debt heterogeneity may influence variable markups. First, if bank debt is costlier, though more flexible than market debt in providing restructuring opportunities, then, for a given leverage ratio, liquidation losses increase with market debt reliance. As more financing is obtained via market debt, I contend firms may be incentivized to set higher markups, both boosting current cash flow and meeting debt liabilities. Second, the trade-off between current and future cash flow through the customer base implies persistently high markups are untenable. An increasing reliance on market debt may be offset by setting high markups to an optimal point. After which, a sustained period of markup reductions is required to rebuild the customer base. The net effect of debt structure on markups then depends on the relative importance of these two channels.

Variable markups may rise for some firms and fall for others, depending on which channel dominates. I study these two channels with granular firm-level data, coupled with estimates of variable markups. I find a novel *hump-shaped* relationship between a firm's markup and its market debt share. On average, variable markups rise with their market debt share, peaking at a share of 61-67% before declining. In addition, a one standard deviation decrease in the market debt share both relative to the mean and below the "peak" is associated with a 4.9% decrease in the markup. This non-linear relationship is robust to various fixed effects and to a refined set of firm-level covariates.

Essentially, the "peak," or turning point, of this hump shape increases with either a firm's leverage or customer base. This is intuitive for several reasons. First, a firm's need to generate internal financing by raising its markup should increase with its level of outstanding,

[4] The importance of customer base formation is at the heart of theoretical works on customer markets, which represent notable features of major industries across the U.S. economy, from retail to commodity-like markets (Gourio and Rudanko, 2014; Hottman et al., 2014; Foster et al., 2016).

non-renegotiable market debt. The higher its outstanding market debt balance, the less flexibility the firm has, and the more leveraged it becomes. A highly-leveraged firm with a market debt share close to one will raise its markup today, to generate internal financing. However, a firm with a similar share, but very little debt, will not find it optimal to sacrifice its customer base by raising its markup, due to its liabilities being low. It places more weight on the future benefit of new and locked-in customers.

Second, firms with a relatively large customer base can make more profits on their locked-in customers with higher markups. This enables financing of a greater level of debt. Be that as it may, "every customer counts," and a firm with too few customers must think twice about raising its markup. Regardless of a firm's market debt share, a low customer base means its markup can only be increased by so much, before it no longer has customers to sell.

With these empirical results in mind, I provide a partial equilibrium framework rationalizing this observable, hump-shaped structure. Building on the discrete-time, "trade-off" theory-based formulations of Hackbarth et al. (2007) and Crouzet (2017), I develop a dynamic, structural model of the firm in which external financing occurs through issuances of bank loans and market debt. Bank and market debt differ along two dimensions. On the one hand, unlike market debt, bank debt is special in providing flexible lending terms through renegotiation. On the other hand, bank debt is costly in comparison to market debt. This occurs because a bank's flexibility comes at the expense of higher funding costs.

Within my model, firms operate in a customer market as monopolistic competitors setting prices as markups over marginal costs. To produce, firms combine capital and a flexible factor according to a technology subject to idiosyncratic risk. Firms carry outstanding bank and market debt principals from the previous period. Capital investment, variable costs, and debt payments are financed using realized operating profits, as well as by issuing one-period bank and market debt. Firms have limited liability – they can default on outstanding debt – in which case their assets are liquidated. Firms are then forced to exit the economy. Still, a firm's total debt level is always constrained, because floating either type of debt incurs convex issuance costs, and liquidation entails deadweight losses.[5]

At the core of this equilibrium relationship are the trade-offs between bank and market debt. These trade-offs interact with inefficient liquidation losses, along with a demand accumulation process occurring through the customer base. Thus, my model features the two competing channels highlighted earlier.

The customer base acts as a demand shifter in my model. As a result, when setting today's markup, a firm balances current and future demand. However, a low capital stock and a debt structure tilted towards market debt elevates liquidation losses. This occurs because operating profits are low, overall leverage is high, and market debt cannot be restructured. Under these circumstances, and if the firm's demand is already high, the marginal value of an additional dollar generated by raising its markup exceeds future losses in customers.

[5]Boileau and Moyen (2016) and Belo et al. (2018) are two recent works with structural corporate finance models that incorporate convex adjustments costs to varying the debt level.

Thus, the firm is motivated to offset its rigid, market debt contract with a high markup by putting less weight on the future benefit of its customers. This channel generates the upward-sloping part of this hump shape.

If a firm's demand is already low, raising its markup would further deplete its customer base, inevitably forcing it into liquidation, regardless of its market debt share. The cost associated with further depleting tomorrow's customer base exceeds today's benefit of a high markup. This incentivizes the firm to attract new customers by cutting its markup, whilst staving off liquidation. The downward-sloping portion of this hump shape is generated by this second channel.

To solve numerically, I recast my heterogeneous agent model in continuous time. This enables me to exploit efficient methods recently introduced in Achdou et al. (2017). Because my model features a non-convexity arising from the firm's choice between liquidation, restructuring, and normal debt repayment, the numerical algorithm in Achdou et al. (2017) offers several computational advantages for these types of problems, relative to traditional, discrete-time methods. Most notably, I obtain numerical solutions in short time.

I parametrize and calibrate the model by matching key moments from the pre-2008 sample of public U.S. firms studied in my empirical work. The model generates an endogenous stationary distribution of firms that vary across differences in customer base and capital, as well as outstanding bank and market debt liabilities. Firms sort themselves into their optimal debt structures and markup strategies along this cross-sectional distribution. Because firms exit if liquidation is triggered, entry and exit dynamics are a necessary feature of my model. This enables me to generate a distribution that is not driven by survivorship bias.

Consistent with my empirical finding, the model replicates an observable hump-shaped structure between a firm's variable markup and its market debt share, while matching several key, cross-sectional and aggregate features of the data. The model's hump shape exhibits an optimum market debt share of 60.8%, indistinguishable from the "peak" share, observed in the data, of 61%. As in my sample, this hump-shaped relationship is rejected by firms with low leverage ratios, though it cannot be rejected by highly-leveraged firms. In addition, the "peak" is smaller for firms with a low customer base, relative to high-customer base firms, tantamount to my empirical findings.

In the remaining portions of this chapter, I use my model as a laboratory to study the perfect foresight response of firms to a one-time, exogenous shock to the bank credit supply. My experiment aims to replicate the bank credit crunch during the 2008-09 financial crisis in the United States. I do this by matching the average market debt share of public U.S. firms, which rose from 50.1% in 2007 to 52.9% in 2010. In response to the shock, the hump shape's "peak," or optimum share, increases from 60.8% to 65.1%. This suggests across the distribution of firms, the average benefit of raising markups to generate additional internal financing grows. This occurs because most firms move into market debt as a result of bank debt becoming costlier, though at the expense of less flexibility in their cash flows.

In the aggregate, the average variable markup exhibits a modest spike, while total sales decline by 8.5%. By comparison, the average variable markup of public U.S. firms rises by less than 1% around the crisis, and their total sales decline considerably by 11.8%. As a result, this bank credit shock explains roughly 75% of the observed fall in total sales by public U.S. firms borrowing from both banks and markets.

The rest of this chapter is organized as follows: I begin by briefly discussing my contributions to related literature in **Section 1.2**. **Section 1.3** touches on the data used in this chapter. **Section 1.4** addresses the main research design and presents the reduced-form evidence. **Section 1.5** introduces the dynamic model of heterogenous firms in discrete time. **Section 1.6** performs quantitative analyses, and demonstrates my model's ability to generate a hump shape between variable markups and market debt shares. In this section, I also assess the model's fit. **Section 1.7** explores the response of the model to aggregate shocks, in particular a shock to the bank credit supply. **Section 1.8** concludes with directions for future work. Rising U.S. market concentration is currently one of the most widely discussed topics in both academic and policy spheres (CEA, 2016; De Loecker and Eeckhout, 2017; Gutiérrez and Philippon, 2017; Shapiro, 2018; Hall, 2018). Mirroring this trend is the dramatic expansion in U.S. corporate market debt since 2007.[6] On the heels of this chapter, I intend to relate my distributional analysis to these foregoing macroeconomic developments.

1.2 Related Literature and Contributions

This chapter makes two key literature contributions. To the corporate finance literature, I contribute new empirical and theoretical insight into how debt heterogeneity impacts a firm's mode of financing and conduct in product markets. Debt heterogeneity is a feature of most firms' capital structures, with debt financing consisting largely of a mixture between bank and market finance (Rauh and Sufi, 2010; Adrian et al., 2013; Colla et al., 2013).

The notion that bank lenders provide costlier, though more flexible lending arrangements in comparison to corporate bond markets is at the core of existing works on debt heterogeneity (Gertner and Scharfstein, 1991; Diamond, 1991; Rajan, 1992; Bolton and Freixas, 2000; Hackbarth et al., 2007; De Fiore and Uhlig, 2011). Many of these works examine debt choice explicitly in the context of information asymmetry, efficient renegotiation of debt contracts, and the agency costs of debt.

Several prominent empirical studies examine the cross-sectional determinants of debt financing choice within the context of the aforementioned theoretical works. Most notably, Gilson et al. (1990) and Denis and Mihov (2003) find considerable support for the view that bank debt is more flexible, yet costlier in comparison to market debt. For example, Denis and Mihov (2003) document how bank debt issuances provide greater flexibility over market debt with regards to the timing of borrowing and debt payments.

Most, if not all, of the literature on the relationship between capital structure and competitive performance treats all debt the same. Both my empirical and theoretical frameworks emphasize that whilst a firm's variable markup may be decreasing with its leverage (Brander and Lewis, 1986; Maksimovic, 1988; Lyandres, 2006), it may be increasing with its market

[6] One notable source: Dec. 11, 2018, "Yellen and the Fed are afraid of a corporate debt bubble, but investors still aren't" CNBC.

debt share, in a manner consistent with Chevalier (1995a) and Chevalier (1995b), Chevalier and Scharfstein (1996), and Dasgupta and Titman (1998), among others. In essence, both my theoretical and empirical contributions corroborate the main thesis in Campello (2006), which rests on the notion that debt financing and product market choices are non-linear.

My second contribution is to the macroeconomics literature. Specifically, to works on cross-sectional variable markups, by advancing a new financial theory incorporating both a customer market and heterogeneity in debt structure into a model of firm dynamics.

This chapter is related to a vast literature on customer base dynamics as it relates to the industrial organization and macroeconomic models of firm pricing and search frictions. Among earlier works, Phelps and Winter (1970) study a firm's optimal variable markup in environments where the retention and acquisition of customers is balanced across time through pricing behaviors. A strand of work, starting with Klemperer (1987), Farrell and Shapiro (1988), and Beggs and Klemperer (1992), discuss the role of information frictions, switching costs, and network effects in binding customers to certain firms. This gives rise to the "stickiness" of the customer base in product markets.

Literature examining the role of financial frictions in the determination of product prices, both empirically and theoretically, has stressed the importance of pricing-related decisions as a source of internal financing for financially constrained firms. Recent works include Gilchrist et al. (2017) and Kim (2018). While empirically, I do not rigorously explore the causal impact of the 2008 bank credit crunch on variable markups, like in the two aforesaid works, I do stress the importance of debt structure for determining the equilibrium relationship between a firm's financial position and its variable markup.

This chapter is also related to a rich literature of macroeconomics on firm growth and financial frictions. In my model, the firm's limited liability is a key financial friction, which is a feature I share with the models in Cooley and Quadrini (2001) and Clementi and Hopenhayn (2006), among others. I contribute to this literature by introducing real-world product frictions via a customer market, which interact with endogenous debt financing choices to generate steady-state growth dynamics.

Lastly, the basic structure of my model is most similar to the dynamic investment models in Crouzet (2017), Xiao (2018), as well as Dou and Ji (2017). While the first two ignore both imperfect competition and the customer base, they incorporate the same trade-offs between bank and market debt existing within my model. Whereas, the latter integrates a customer market with costly external equity financing, but ignores debt and credit supply frictions altogether. My model combines the key ingredients from both theoretical frameworks.

1.3 Data Overview

Sample Description

I start by obtaining detailed, annual debt structure data on U.S. firms covered by Standard and Poor's (S&P) Capital IQ (CIQ) Capital Structure Debt files from 1992 to 2016. CIQ provides information about the debt aspect of companies' capital structures dating back to 1992. CIQ's Debt files decompose total debt into seven mutually exclusive types: commercial paper, revolving credit lines, term loans, bonds and notes, capital leases, preferred trusts, and other borrowings. I follow Xiao (2018) and define bank debt as the sum of revolving credit lines and term loans, while market debt is the sum of commercial paper, bonds, and notes. I remove firm-years for which bank debt, market debt, or the sum of both exceeds total debt as reported in CIQ. This initial sample provides me with 297,167 firm-year observations.

I then merge the resulting CIQ sample with firms in S&P's Compustat Fundamentals database, and which are traded on the Amex, Nasdaq, and NYSE. This merge yields 127,051 firm-year observations. I remove regulated utilities (SIC codes 4900-4999), financials (SIC codes 6000-6999), and firms not incorporated in the United States. I do this because this chapter is not intended for explaining the debt financing choices and variable markups of both U.S. regulated utilities and financial corporations. I am left with 78,519 firm-year observations.[7] I then further remove firm-years with negative or zero values for total assets or total sales, and missing historical North American Industry Classification System (NAICS) codes. Following this filtering exercise, I am left with a sample of 73,568 firm-year observations involving 10,643 unique firms.

In constructing annual firm characteristics, I use the same definitions that are standard in the empirical corporate finance literature. Firm-level characteristics are from CIQ, Compustat, the Center for Research in Security Prices (CRSP), along with data contributed and shared by various academic researchers. All continuous firm characteristics are winsorized at the 1^{st} and 99^{th} percentiles by year.[8] Lastly, I follow De Loecker and Eeckhout (2017) and use historical, 5-digit NAICS codes to classify industries.[9]

Tables 1.1, **1.2**, **1.3**, and **1.4** provide detailed definitions of the variables used throughout my empirical analysis. Descriptive statistics for characteristics and other firm-level variables used throughout this chapter are provided in **Table 1.5**.

Estimating Variable Markups

I estimate variable markups using the production-based approach introduced in Hall (1988), and recently implemented in De Loecker and Eeckhout (2017) and Traina (2018). These applications use accounting data extracted from Compustat to estimate the ratio of product price to marginal cost.

This approach computes firm-level markups as the ratio of total sales to variable factor expenditures, scaled by a structural estimate of the variable factor's output elasticity.

[7]Missing observations are replaced by their most recent value, when appropriate. Empirical results in this chapter are robust to dropping missing observations, or linearly interpolating, missing observations with neighboring values.

[8]As a robustness check, I also winsorize continuous firm characteristics at the 5^{th} and 95^{th} percentiles by year. Qualitatively, this does not alter those results presented throughout this chapter. Additional results are available upon request.

[9]Instead of using current, "header" codes, I use historical codes, as these are valid in real-time.

Estimation occurs at an annual frequency, due to there being significantly less variation in elasticities at the quarterly frequency.

The underlying theory for this methodology is parsimonious. It assumes cost minimization of perfectly competitive, variable production inputs, which are free of adjustment costs. It is crucial to point out there is no need to specify a demand system to restrict either the nature of firm competition or how prices are set. I describe the implementation of this estimation procedure in **Appendix A.4**.

Equipped with a structural estimate of the variable factor's output elasticity, the ratio of total sales to variable factor expenditures is measured using Compustat's total sales (SALE) to the cost of goods sold (COGS). COGS constitutes the main component of a firm's operation expenses. It measures the direct variable inputs to production, such as materials and most labor costs.

Recent work by Traina (2018) contends the residual component, SGA (selling, general, and administrative) expenses, may capture other variable costs. SGA expenses measure indirect inputs to production, such as advertisement, marketing, and management. In contrast, Gilchrist and Himmelberg (1998) emphasize a firm's SGA expenses signal fixed costs. A plethora of research from the accounting literature additionally finds SGA expenses may be largely "sticky" (Anderson et al., 2003; Anderson et al., 2007). As a result, there is a debate as to whether SGA expenses are entirely variable, at least in the short term. Even if a fraction of these expenses are variable, the extent to which they are is unclear. Because SGA expenses may include missing portions of a firm's variable costs, as a robustness check, I provide empirical results including them in the estimation of variable markups.[10]

1.4 Research Design: Reduced-Form Evidence

This section presents my main research design, which builds on existing empirical relationships between capital structure and variable markups. These earlier studies, in some form or another, aim to quantify the contemporaneous linkages between firms' corporate financing and price-setting behaviors in output markets through two key firm characteristics: the leverage ratio and the customer base.

I build on this literature, primarily by positing both a new and non-linear relationship between a firm's variable markup $\mathcal{M}$ and its share of outstanding market debt in total debt financing, denoted by $MarketDebtShare$. Total debt financing is defined as the sum of outstanding bank and market debt. In particular, I consider the quadratic specification:

$$\begin{aligned}\mathcal{M}_{i,j,t} = \beta_0 + \beta_1 MarketDebtShare_{i,j,t} + \beta_2 MarketDebtShare^2_{i,j,t} \\ + \beta_3 Leverage_{i,j,t} + \beta_4 SGAX_{i,j,t} + \epsilon_{i,j,t}\end{aligned} \tag{1.1}$$

[10]Variable markups (*with* or *without* SGA expenses) resulting in economically unreasonable estimates are dropped from my sample. This is done by trimming markups at the 10^{th} and 95^{th} percentiles of the distribution, yielding a minimum and maximum variable markup of 0.72 and 2.65, respectively. My results are also robust to trimming estimates at other percentile cutoffs.

for firm i in industry j and year t. The dependent variable is the estimated variable markup, whilst the explanatory variables include $MarketDebtShare$, the (market) leverage ratio $Leverage$, and a proxy for the customer base, denoted by $SGAX$. The idiosyncratic disturbance term is given by $\epsilon_{i,j,t}$.

Because both the leverage ratio and customer base are crucial inputs to firms' variable markup strategies, it is essential that I account for them throughout my analysis. Whilst leverage is directly observed with accounting data, the customer base is not and can be difficult to quantify. However, Gourio and Rudanko (2014) and Rudanko (2017b) argue that high SGA expenses are indicative of the extent to which a firm operates in an industry with a customer market. This is directly related to cross-sectional variation in the customer base. At the firm-level, the ratio of SGA expenses to sales, $SGAX$ ratio, provides a proxy for a firm's customer base, because the stock and loyalty of existing customers is critically linked to the costs of attracting new customers.

Before describing the results obtained from the estimation of regression specification (1.1), particularly the estimates of β_1 and β_2, I briefly re-establish past works' findings on the importance of both overall leverage and the customer base for variable markups.

Panels (A) and (B) of **Figure 1.1** present a non-parametric estimate of the conditional expectation of variable markup $\mathcal{M}$ as a function of $Leverage$ and $SGAX$, after residualizing each variable from the other explanatory variables included on the right hand side of specification (1.1). This non-parametric estimate is shown as a binned scatterplot. For each relationship, the best linear OLS fit of these residuals is also provided. This corresponds to parametric estimates of coefficients β_3 and β_4.

Panel (A) provides strong evidence of a linear yet negative relationship between a firm's markup and its leverage ratio. This is consistent with the insights of Brander and Lewis (1986) and Lyandres (2006): as a firm accumulates more debt relative to its assets, it becomes more aggressive by setting a lower markup. The estimate of β_3 is, at the 1% level, statistically and economically significant.

Panel (B) presents a substantially linear yet positive relationship between a firm's markup and its customer base, as proxied by a firm's SGA expenses over sales. This finding lends support to the notion that firms with a larger customer base are able to set higher markups precisely because they have more loyal and valuable customers. This result is consistent with the theoretical predictions in Rudanko (2017a). In that model, variable markups are set each period in a customer market where firms with more existing customers set higher prices despite attracting fewer new customers.

Both results shown in **Figure 1.1** are robust to the inclusion of (5-digit) NAICS industry fixed effects, year fixed effects, and a refined set of firm characteristics acting as control variables. They are provided in **Figure A.1** of **Appendix A.1**. The additional set of firm-level characteristics are taken directly from various works in the corporate finance literature. They include the lagged markup, size (measured using log of real book assets or sales), age, sales growth, the market-to-book asset ratio, cash holdings, asset tangibility, profitability, the interest rate coverage ratio, an indicator equal to 1 if dividends were paid out in the current year; but 0 otherwise, the Whited and Wu (2006) index, and the Bodnaruk et al. (2015)

text-based analysis measure of financial distress.[11] In line with prior empirical evidence, each firm characteristic included as a control variable has been shown to be correlated with leverage, debt structure, or the markup.[12]

I now establish the importance of a firm's debt structure. This is one of my chapter's main contributions. I perform the same exercise as before, estimating the non-parametric conditional expectation of variable markup $\mathcal{M}$ as a function of $MarketDebtShare$ after residualizing from $Leverage$ and the $SGAX$ ratio.

Panel (A) of **Figure 1.2** summarizes the results using a binned scatterplot. The residuals exhibit a quadratic structure. The best quadratic OLS fit of these residuals is shown, which corresponds to estimates of coefficients β_1 and β_2 in (1.1). Both estimates of β_1 and β_2 are highly, statistically significant at the 1% level, and provide strong evidence in favor of a hump-shaped structure between a firm's variable markup and its market debt share. On average, there is a hump-shaped relationship between markups and market debt shares, with the "peak" at a share of 67%. This "peak" is also highly, statistically significant at the 1% level (Column (1) of **Table 1.6**), and is robust to the same fixed effects and firm-level covariates included in the previous analysis of $Leverage$ and $SGAX$. This robustness check is provided in Column (1) of **Table A.1** in **Appendix A.2**. The hump shape also remains intact, even after restricting my sample to the period before the financial crisis, from 1992 to 2007, albeit the "peak" share falls to 61% (Column (1) of **Table A.2** in **Appendix A.2**).

I also gauge the estimated structure of this hump-shaped pattern by plotting the quadratic relationship between the variable markup and the market debt share for the average firm in Panel (B) of **Figure 1.2**. Across the full range of market debt shares, the 95% confidence intervals around the quadratic relationship's point estimates are tight. This suggests the hump-shaped structure is statistically different from zero for all feasible $\mathcal{M}$-$MarketDebtShare$ pairs. Moreover, a one standard deviation decrease in the market debt share both relative to the mean and below the "peak" of 67% is associated with a 4.9% decrease in the markup.

The Interaction Between Debt Structure and Leverage

The hump shape motivated by specification (1.1) is a quadratic relationship estimated across *all firms* in my sample. Since the leverage ratio and the customer base are each individually necessary, it is essential to first understand whether the non-monotonicity between markups and debt structures varies across firms with different levels of financial leverage.

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[11] I also include binned, fixed effects for a firm's S&P credit rating by following Rauh and Sufi (2010). I do this by splitting firms into four groups, based on their S&P credit rating: (i) A or above, (ii) BBB, (iii) BB, and (iv) B or below.

[12] Both Rauh and Sufi (2010) and Colla et al. (2013) document how low-credit quality firms (BB or lower) employ, on average, more secured debt in the form of bank loans, as well as subordinated debt in the form of subordinated bonds and convertible debt in comparison to high-credit quality firms (BBB or higher). Moreover, firms with more growth opportunities and cash holdings tend to specialize in one debt type, while more profitable firms and firms with more tangible assets tend to mix more between bank and market debt. Since both financial constraints and distress may impact a firm's ability to issue one debt security over another, I also control for this in my analysis.

A firm's need to generate internal financing by raising its markup should become increasingly important with its level of outstanding, non-renegotiable market debt. This occurs because a firm becomes more leveraged, and its debt structure less flexible. If a firm has a market debt share close to one, but has very little debt relative to its assets, it should not be incentivized to raise its operating profits by setting a higher markup. Instead, it should lean more towards both locking-in current customers and attracting new ones by lowering its markup. This implies the "peak" of the hump shape should increase with leverage. If the reverse were true, this would raise doubts about the main results.

To test my hypothesis, I sort firms into quartiles based on the leverage ratio by year. I define firms in the lowest and highest quartile as the set of low- and highly-leveraged firms, respectively. Having binned firms in this manner, I estimate the following specification for low- and high-leverage firms:

$$\begin{aligned}\mathcal{M}_{i,j,k,t} &= \beta_0 + \beta_1 MarketDebtShare_{i,j,k,t} + \beta_2 MarketDebtShare^2_{i,j,k,t} \\ &\quad + \varrho SGAX_{i,j,k,t} + u_{i,j,k,t}\end{aligned} \tag{1.2}$$

for firm i in industry j, year t, and bin $k = \{\text{low leverage, high leverage}\}$.

By restricting my sample in this manner, I show the null of a hump-shaped structure is rejected by low-leveraged firms, but cannot be rejected by highly-leveraged firms. This is shown graphically in Panels (A) and (B) of **Figure 1.3**, as well as Columns (2) and (3) of **Table 1.6**. **Figure 1.3** shows the hump shape is not statistically different from zero for firms with a low leverage ratio, but is statistically significant at the 1% level for highly-leveraged firms and peaks at a share of 49.1%. These results are robust to fixed effects and the same set of firm-level covariates from before (see **Appendix A.2**).

In terms of economic importance, within the set of highly-leveraged firms, a one standard deviation decrease in the market debt share both relative to the mean and below the "peak" of 49.1% is associated with a 3.9% decrease in the markup (see **Figure A.3** in **Appendix A.1**).

The Interaction Between Debt Structure and the Customer Base

By comparing firms across the customer base, I further verify the soundness of my results. Intuitively, firms with a relatively larger customer base can make more profits on their existing customers by setting higher markups. This enables them to internally finance and offset the rigidity of their debt structure, arising from their inability to restructure market debt.

However, if a firm has a low customer base, it must think twice about raising its markup. Despite having a high market debt share, a firm with a low customer base can only increase its markup today by so much before it potentially has no customers to sell to tomorrow. As the level of the customer base increases, this intuition implies the quadratic relationship between $\mathcal{M}$ and $MarketDebtShare$ should peak at a relatively higher share. Firms with a larger customer base place less weight on the future benefit of both new and locked-in customers, and more weight on the benefits of front-loading cash flow.

To compare firms across customer base, I follow Gourio and Rudanko (2014). I first take the time-series average of each firm's $SGAX$ ratio and split firms below and above the median based on this time-series average. Firms below and above the median represent low- and high-customer base firms, respectively. In **Table 1.7**, I provide some examples of notable firms within each group. Following a similar empirical structure as before, I estimate the following specification:

$$\begin{aligned}\mathcal{M}_{i,j,k,t} &= \beta_0 + \beta_1 MarketDebtShare_{i,j,k,t} + \beta_2 MarketDebtShare^2_{i,j,k,t} \\ &\quad + \xi Leverage_{i,j,k,t} + v_{i,j,k,t}\end{aligned} \tag{1.3}$$

for firm i in industry j, year t, and bin $k = \{\text{below median, above median}\}$.

Both panels of **Figure 1.4** show the hump shape peaks at a *lower* market debt share for firms below the median average $SGAX$ ratio, relative to firms above the median. This is also clear from the results shown in Columns (4) and (5) of **Table 1.6**. Low-customer base firms exhibit a "peak" share of 58.6% in comparison to a "peak" of 75.1% for high-customer base firms. Moreover, the null of the equality in both groups' "peak" shares is rejected using a Wald test. These results are also robust to both industry and year fixed effects, as well as to the same set of firm controls used in previous robustness checks.

There are also stark differences between both sets of firms in terms of economic significance. For the average, high-customer base firm, a one standard deviation decrease in the market debt share both relative to the mean and below the "peak" of 75.1% is associated with a 6.4% decrease in the markup. This is in contrast to the observed 1.7% decrease in the markup for an average, low-customer base firm with a "peak" share of 58.6% (see **Figure A.5** in **Appendix A.1**).[13]

Main Takeaways

My estimates document a robust, hump-shaped structure between variable markups and market debt shares. The importance of the market debt share increases with a firm's accumulation of debt over its assets, as well as its stock of customers. This structure is both highly, statistically significant and economically meaningful.[14] I postulate the economic

[13] Frictions in the product market make a customer base "sticky." As a result, a firm's customer base can be related to the percentage of the total product market it captures. This percentage is measured using the market share of sales within a firm's industry. In line with earlier works studying the linkages between a firm's leverage ratio and pricing behavior through the market share of sales (Chevalier, 1995a; Chevalier, 1995b; Chevalier and Scharfstein, 1996), I repeat the aforementioned analysis by sorting firms based on the *median* market share of sales, denoted by $SalesShare$. These results are aligned with my findings based on splitting firms below and above the median (time-series average) $SGAX$ ratio.

[14] I also provide the same set of results with variable markups estimated *including* SGA expenses in the measure of a firm's total variable costs. These results are provided in **Figures A.11** through **A.18** of **Appendix A.1** and **Tables A.3** through **A.5** of **Appendix A.2**. Qualitatively, accounting for SGA

mechanisms driving this hump shape derive from two channels: (1) a firm's incentive to generate internal financing and boost current cash flow by setting high markups, specifically when its debt structure is tilted more towards cheaper, but less flexible market debt, along with (2) the trade-off between current and future profits in customer markets.

The first channel generates an increasing relationship between the variable markup and the market debt share at *low* shares. Whereas, the second channel generates a decreasing relationship between the markup and the market debt share at *high* shares. The "peak" of this hump shape characterizes the market debt share at which both competing channels are optimally balanced.

In the next section, I embed these two channels in a dynamic, partial equilibrium model of firm heterogeneity. This modeling device will provide a theoretical foundation for my novel set of results.

1.5 Theory: A Model of Variable Markups and Debt Structure

To rationalize my empirical findings, I develop an infinite-horizon, partial equilibrium model of firm investment, debt financing, and variable markups. I do this by building on the discrete-time, "trade-off"-theory based formulations of Hackbarth et al. (2007) and Crouzet (2017).

A continuum of firms operate in a customer market as monopolistic competitors setting prices as markups over marginal costs. Production occurs by combining physical capital with a flexible factor. Firms carry with them outstanding bank and market debt principals from the previous period. They can finance capital investment, variable expenditures, and debt payments using realized operating profits, in addition to new issuances of both one-period bank loans and market debt.

Firms are managed by a set of risk-neutral shareholders, who are residual claimants to high earnings, whilst protected from losses by limited liability. If a firm chooses to default on its outstanding debt liability, its assets are liquidated at a deadweight loss, then distributed to creditors. Whereas, if a firm chooses to continue operations, it does so by fulfilling its promise to repay total outstanding debt, or by attempting to renegotiate its outstanding bank debt payment. In the absence of liquidation or renegotiations, interest expenses on both bank and market debt have a tax advantage. Debt capacity is finite and curtailed by both inefficient liquidation losses and convex debt issuance costs.

Each period, firms are heterogenous in their customer base, stock of capital, as well as outstanding bank and market debt principals. However, firms also differ in their productivity, which is their only source of uncertainty. Shareholders maximize their present, discounted

expenses leaves the results unchanged. Overall, my estimates are stable, suggesting the observable hump-shaped relationship is not an artifact of the specific way in which I construct variable markups.

stream of cash flows by choosing (i) product prices, (ii) investment, as well as (iii) new issuances of bank and market debt.

Section 1.5.1 presents the model's structure. First, I specify a firm's production technology and capital accumulation process. Second, I discuss the product market frictions generating the customer market, as well as the demand curve. I then go over a firm's profits and financing between bank and market debt, settlements of debt contracts, and its optimization problem. Subsequently, I analyze bank and market lenders' pricing of debt. I conclude, by characterizing the economy's stationary equilibrium. Throughout, a *prime* indicates a variable in the next period.

Section 1.5.2 describes my calibration strategy and parametrization of the model's key structural parameters. Finally, **Section 1.5.3** touches on the numerical solution techniques used to solve the model, with details provided in the **Online Appendix**.

1.5.1 Model Exposition

Production Technology and Capital Investment

Each firm combines capital k, and a flexible factor of production v to produce output according to a constant returns to scale (CRS), Cobb-Douglas production function:

$$y = zk^{\alpha}v^{1-\alpha} \tag{1.4}$$

with $\alpha \in (0, 1)$ representing the capital share. Idiosyncratic productivity z is uncertain, and follows a Poisson process, taking on two-states i.e. $z \in \{z_1, z_2\}$, with $z_2 > z_1 > 0$. Poisson intensities for states z_1 and z_2 are denoted by λ_1 and λ_2, respectively, while transition probabilities are represented by $\mathbb{P}\left(z' \middle| z\right)$. Both inputs to production are perfectly competitive. In addition, the variable factor is free of adjustment costs, making it a static input to production.

Investment in capital i is defined as the difference between the next period's capital stock and the current capital stock after depreciation:

$$i \equiv k' - (1 - \delta) k \tag{1.5}$$

with $\delta \in (0, 1)$ denoting the depreciation rate. Each firm purchases and sells capital at a price of one, incurring adjustment costs given by

$$A(i, k) \equiv \frac{a}{2}\left(\frac{i}{k}\right)^2 k \tag{1.6}$$

The functional form of (1.6) is standard in corporate finance models of investment. The convex cost is quadratic in the ratio of investment to capital, implying the adjustment cost scales up with the capital stock. The parameter a is positive, and encompasses smooth adjustment costs, which are consistent with observed dynamics of firm investment. A large value of a indicates both smoother investment demands and high capital resale costs (Cooper and Haltiwanger, 2006).

Customer Market

Each period, customers observe prices charged by the firm from which they purchased goods in the previous period. Switching to a new supplier of any good incurs a brand switching cost, in line with search models of product markets (Klemperer, 1987; Farrell and Shapiro, 1988; Beggs and Klemperer, 1992). Customers naturally interact with each other to compare prices across firms, and must then decide whether to change suppliers. Over time, customers gradually shift from firms charging higher to those charging lower prices. Each firm has rational expectations as it observes the flow of customers purchasing its product. This flow is given by the customer accumulation equation:

$$\mu' = \left(1 - \gamma \left(p - \widetilde{P}\right)\right) \mu, \ \mu > 0 \tag{1.7}$$

Variable p is the product price charged by a given firm, $\widetilde{P}$ is the economy-wide, average price of the product, μ is the customer base, and $\gamma > 0$ is the parameter governing frictions in the product market. These frictions are characterized by the costs customers must pay to switch firms. Without loss of generality, I normalize the economy-wide price $\widetilde{P}$ to one.

The customer flow relationship in (1.7) closely follows the linearized formulation in Gottfries (1986), which builds on the non-linear model in Phelps and Winter (1970). When a firm sets $p = 1$, equation (1.7) implies $\mu' = \mu$. Thus, a firm can retain its locked-in customer base. On the other hand, if $p > 1$ or $p < 1$, then a firm loses or gains customers, respectively, in the next period.

Change in the customer base is proportional to a firm's current customer base. This implies a short term change in p will have permanent effects on tomorrow's stock of customers μ'. Because the marginal change in tomorrow's customer base, due to a change in price, is given by

$$\frac{\partial \mu'}{\partial p} = -\gamma p \mu \tag{1.8}$$

tomorrow's stock of customers is decreasing in today's price, with the sensitivity given by γ. As γ decreases, the costs customers must pay to switch from one firm to another increase. This enables firms to post higher prices today, without facing as much of a loss in tomorrow's customers.

Demand Curve

In the customer market, firms operate as monopolistically competitive producers, facing iso-elastic, downward-sloping demand curves:

$$y = \mu \left(\frac{p}{\widetilde{P}} \right)^{-\eta} \tag{1.9}$$

Variables p, $\widetilde{P}$, and μ are the same as before, with $\widetilde{P}$ normalized to one. The economy-wide, price elasticity of demand is given by parameter $\eta \in (1, \infty)$.

Monopolistic competition in a customer market provides firms some short-term market power over their locked-in customers. This implies a firm's pricing behavior is bounded relative to that of its competitors. As a result, prices and quantities will be clustered over narrow ranges, justifying the use of an iso-elastic demand structure.

Operating Profits and Debt Financing

With monopolistic competition, and the demand system in (1.9), a firm's revenue from operations is given by $py = \mu p^{1-\eta}$. Since capital investment is subject to a one-period time-to-build, investment in today's capital was paid for in the previous period. I let w denote the steady-state price of variable input v. Static optimization of v implies a firm's profits become

$$\pi = py - wv = (p - c(p))\, \mu p^{-\eta} \tag{1.10}$$

with c representing marginal costs given by expression $c(p) = \left(\frac{w}{1-\alpha}\right)\left(\frac{1}{zk^{\alpha}}\right)^{\frac{1}{1-\alpha}} \left(\mu p^{-\eta}\right)^{\frac{\alpha}{1-\alpha}}$. This implies the variable markup is $\mathcal{M} = \frac{p^*}{c(p^*)}$, with p^* denoting the optimal product price chosen by a firm. I discuss the optimal product price in the next section.

Whilst the customer base μ is directly related to a firm's demand curve through (1.9), it can also be related to the value of a firm's customer base, as in Gourio and Rudanko (2014). Thus, I define the model-implied $SGAX$ ratio as $SGAX = \frac{\mu}{Sales}$, with $Sales = py = \mu p^{1-\eta}$.

At every date, a firm is required to repay bank and market debt principals (denoted by b and m, respectively) borrowed in the previous period. A firm must also make interest payments on each debt claim, given by $r_b b$ and $r_m m$, with r_b and r_m representing the net interest rate on bank and market debt, respectively.

Firms can finance investment, variable expenditures, and required debt payments using the profits realized from operations, as well as with new issuances of both one-period bank loans and market debt. I assume firms are not allowed to issue external equity, which is reasonable, given the rarity of seasoned equity offerings observed in public U.S. firms (Hackethal and Schmidt, 2004; DeAngelo et al., 2010).[15]

[15] Relative to debt and internal resources (e.g. retained earnings), external equity issuance accounts for only a small share of funds used by public U.S. firms for investment. See **Figure A.19** in **Appendix A.1**.

New issuances of bank loans l_b, and market debt l_m incur issuance costs with a common functional form:

$$\Phi\left(l_b, b\right) = \frac{\phi}{2}\left(\frac{l_b}{b}\right)^2 b$$
$$\Phi\left(l_m, m\right) = \frac{\phi}{2}\left(\frac{l_m}{m}\right)^2 m \tag{1.11}$$

The convex cost in (1.11) is quadratic, reflecting the observed convexity in debt financing costs studied in Altınkılıç and Hansen (2000) and Leary and Michaely (2011). In observation of how the empirical analysis in these two seminal works makes no distinction between debt types, parameter $\phi > 0$ is the same in my model if a firm issues a bank loan or a corporate bond. This cost framework captures the fact that adjusting capital structure is costly, whilst the convexity in issuance costs implies a persistent debt growth process, consistent with my data.[16]

In accordance with Crouzet (2017), the terms of new contracts l_b and l_m are agreed upon before a firm's idiosyncratic risk z is realized. As a result, contracts cannot be indexed to productivity. However, financial intermediaries observe a firm's customer base, capital stock, and outstanding debt principals, so lending will depend on (μ, k, b, m). Similar to the exposition in Crouzet (2017), the dependence of lending contracts on (μ, k, b, m) is omitted throughout this chapter for notational convenience. Descriptions of assumptions governing bank and market lenders' behavior follow my discussion of the firm's problem.

Recursive Formulation of the Firm's Problem

Corporate profits realized from operations are taxed at rate $\tau_c \in [0, 1]$. Due to the equal treatment of interest-bearing debt in the U.S., bank and market debt are given identical tax treatment.[17] Thus, whenever a firm fulfills its promise to repay debt payments, interest expenses may be deducted at interest income tax rates τ_b and τ_m, such that the common rate is given by $\tau_b = \tau_m = \tau_d \in [0, 1]$. Without loss of generality, I assume tax shields come at the expense of bank and market lenders.

Before the settlement of debt payments, earnings before interest after taxes (and depreciation), EBIAT, is defined as

$$EBIAT = \left(1 - \tau_c\right)\pi - i - A\left(i, k\right) + l_b + l_m - \Phi\left(l_b, b\right) - \Phi\left(l_m, m\right) \tag{1.12}$$

This expression for $EBIAT$ relates a firm's operating profits, investment and its cost, as well as debt issuances and their costs, in close accordance with its standard calculation on a public U.S. corporation's income statement. A notable difference is the inclusion of new

[16] A similar, convex issuance cost function is utilized in Boileau and Moyen (2016) and Belo et al. (2018).

[17] Source: Overview Of The Tax Treatment Of Corporate Debt And Equity, The Joint Committee on Taxation, U.S. Congress.

debt issuances and their costs, which generate an immediate net inflow of funds for a firm, but do not require any repayment with interest until the next period.

Given realized operating profits, a firm chooses (i) product prices p, (ii) investment i, and (iii) new issuances of bank and market debt l_b and l_m together with its debt settlement decision. More specifically, a firm may choose to default on its required debt payments, which include interest payments along with outstanding bank and market debt principals from the previous period, or choose to stay active. If the latter is chosen, the firm must fulfill its obligation to pay required debt payments, or attempt to renegotiate its required bank debt payment $(1 + r_b)\, b$.

Therefore, each period, the value of a firm is the maximum between the value of liquidating $\mathbf{V}^l$, the value of repayment following a bank debt restructuring $\mathbf{V}^r$, and the value of normal debt repayment $\mathbf{V}^p$:

$$\mathbf{V}(\mu, k, b, m, z) = \max\left\{\mathbf{V}^l, \mathbf{V}^r, \mathbf{V}^p\right\} \tag{1.13}$$

In accordance with Hackbarth et al. (2007) and Crouzet (2017), I assume liquidation entails deadweight losses. This implies remaining proceeds distributed to both creditors and shareholders are a fraction $\chi \in \left(0, 1\right]$ of $EBIAT$. This is reasonable, given results reported in Bris et al. (2006), which documents a decrease in post-liquidation asset values across a sample of 225 Chapter 11 filings between 1995 and 2001.

Liquidated assets are distributed according to a seniority rule consistent with the Absolute Priority Rule (APR) governing Chapter 7 proceedings in the United States.[18] Under this priority structure, bank debt is senior to market debt, making shareholders the residual claimants. Therefore, the payoff to bank and market lenders are $\min\{\chi EBIAT, (1 + r_b)\, b\}$ and $\min\{\max\{0, \chi EBIAT - (1 + r_b)\, b\}, (1 + r_m)\, m\}$, respectively. A firm's residual payoff is then given by

$$\mathbf{V}^l = \max\{0, \chi EBIAT - (1 + r_b)\, b - (1 + r_m)\, m\} \tag{1.14}$$

Because liquidation is chosen optimally, occurring whenever $\mathbf{V}^l = \max\left\{\mathbf{V}^l, \mathbf{V}^r, \mathbf{V}^p\right\}$, the value of liquidating must be zero, $\mathbf{V}^l = 0$. Consequently, a firm is forced to exit the economy.

If a firm attempts to renegotiate its required bank debt payment, then the restructured payment is given by $\chi EBIAT$. This is justified on two grounds. First, banks are guaranteed $\chi EBIAT$ if liquidation is trigged by the firm. As a result, $\chi EBIAT$ is the minimum a bank is willing to accept as a payment in any renegotiation. Second, optimality requires a firm to offer a value-maximizing payment in a renegotiation, which is subject to the bank's participation constraint. As a consequence of these two results, the restructured claim must be given by $\chi EBIAT$. With only the required bank debt payment able to be restructured, a firm's market debt payment in the current period, $(1 + (1 - \tau_d)\, r_m)\, m$, must remain unaltered in a renegotiation.

[18] White (1989) provides institutional background on the APR structure.

Finally, if a firm chooses to honor standing contracts with its lenders, required debt payments are made. These repayments are comprised of the principal borrowed last period, along with tax-deductible interest payments, $(1 + (1 - \tau_d) r_b) b + (1 + (1 - \tau_d) r_m) m$.

The value of repayment following a restructuring of bank debt, along with the value of normal debt repayment, can be written recursively with the Bellman equation:

$$\mathbf{V}^j (\mu, k, b, m, z) = \begin{cases} \max\limits_{\{p,i,l_b,l_m\}} \big\{ EBIAT - \chi EBIAT & \text{if } j = r \text{ (restructuring)} \\ \qquad - (1 + (1 - \tau_d) r_m) m & \\ \qquad + \left(\frac{1}{1+r}\right) \mathbb{E}_{z'|z} \left[\mathbf{V} (\mu', k', b', m', z') \right] \big\} & \\ & \\ \max\limits_{\{p,i,l_b,l_m\}} \big\{ EBIAT - (1 + (1 - \tau_d) r_b) b & \text{else if } j = p \text{ (repayment)} \\ \qquad - (1 + (1 - \tau_d) r_m) m & \\ \qquad + \left(\frac{1}{1+r}\right) \mathbb{E}_{z'|z} \left[\mathbf{V} (\mu', k', b', m', z') \right] \big\} & \end{cases} \tag{1.15}$$

subject to

$$EBIAT \geq \begin{cases} \chi EBIAT + (1 + (1 - \tau_d) r_m) m & \text{if } j = r \text{ (restructuring)} \\ & \\ (1 + (1 - \tau_d) r_b) b + (1 + (1 - \tau_d) r_m) m & \text{else if } j = p \text{ (repayment)} \end{cases} \tag{1.16}$$

$$\mu' = (1 - \gamma (p - 1)) \mu, \;\; \gamma > 0$$

$$k' = (1 - \delta) k + i, \;\; \delta \in (0, 1)$$

$$b' = l_b \tag{1.17}$$

$$m' = l_m \tag{1.18}$$

$$z' \in \{z_1, z_2\} \;\; \text{two-state Poisson process with intensities } \lambda_1, \lambda_2$$

with $EBIAT$ given by equation (1.12).

If the firm restructures its required bank debt payment, the inequality constraint on $EBIAT$ in (1.16) captures both the unaltered, required debt payment made to the market lender, and the firm's inability to extract cash flows from shareholders by issuing equity. This latter restriction also applies in the event of normal debt repayment, captured by the second case presented in (1.16). Finally, bank and market debt obligations from the previous period are settled today, so new outstanding bank and market debt principals are given by (1.17) and (1.18).

Lenders' Debt Pricing Problem

Following Crouzet (2017), bank and market lenders operate in perfectly competitive debt markets, with a common (gross) opportunity cost of funds. This common cost is equal to the gross, risk-free rate, $R = 1 + r$. Perfect competition implies that each type of lender, in equilibrium, makes zero expected profits on its loans. The equilibrium, promised debt payments to bank and market lenders in the next period, denoted by D_b and D_m, must satisfy:

$$\mathbb{E}_{z'|z}\left[\widetilde{D_b}\left(\mu, k, b, m, z, D_b, D_m, z'\right)\right] = \left(1 + \left(1 - \tau_d\right) r_b\right) b' \tag{1.19}$$

$$\mathbb{E}_{z'|z}\left[\widetilde{D_m}\left(\mu, k, b, m, z, D_b, D_m, z'\right)\right] = \left(1 + \left(1 - \tau_d\right) r_m\right) m' \tag{1.20}$$

with b' and m' representing the next period's outstanding bank and market debt principals. If bank debt restructuring is successful, or normal debt repayment occurs, then $b' = l_b$ and $m' = l_m$. However, if a firm chooses liquidation, then $b' = m' = 0$.

For debt type $j \in \{b, m\}$, expression $\widetilde{D_j}\left(\mu, k, b, m, z, D^b, D^m, z'\right)$ represents the gross return for each lender type. Individual returns depend on current states (μ, k, b, m, z), as they determine a firm's $EBIAT$. Debt contracts also depend on the realization of next-period's productivity z', due to its direct impact on the firm's continuation value.

The lending menu, denoted by $\mathcal{L}\left(\mu, k, b, m, z\right)$, is defined as the set of all debt contracts $(l_b, l_m) \in \mathbb{R}_+^2$, for which there exists a *unique* solution to the system of equations governed by (1.19) and (1.20). Thus, the lending menu is the set of all *feasible* debt contracts for a firm with given states (μ, k, b, m, z). $\mathcal{L}\left(\mu, k, b, m, z\right)$ can be partitioned into two non-empty and compact subsets: $\mathcal{L}_K\left(\mu, k, b, m, z\right)$ and $\mathcal{L}_R\left(\mu, k, b, m, z\right)$. In the first subset, $\mathcal{L}_K\left(\mu, k, b, m, z\right)$, contracts (l_b, l_m) imply debt liabilities (D_b, D_m), such that bank debt restructuring occurs with a positive probability. In the second subset, $\mathcal{L}_R\left(\mu, k, b, m, z\right)$, contracts (l_b, l_m) imply debt liabilities (D_b, D_m), such that bank debt restructuring never occurs.

Proposition 1 in **Appendix A.6** touches on the existence of solutions to equations (1.19) and (1.20), as well as the partitioning of set $\mathcal{L}\left(\mu, k, b, m, z\right)$.

Intermediation costs per unit of bank and market debt are represented by positive parameters γ_b and γ_m. The intermediation spread between bank and market debt, $r_b - r_m$, is assumed to be positive, with r_m and r_b defined by:

$$\begin{aligned} r_m &= r + \gamma_m \\ r_b &= r + \gamma_b \end{aligned} \tag{1.21}$$

and $\gamma_b - \gamma_m > 0$. This wedge captures the economy's relative equilibrium bank credit supply (Crouzet, 2017; Xiao, 2018).

The restriction I just laid out is consistent with differences in the regulatory treatment of banks and market-based intermediaries, as well as monitoring costs associated with bank lending (Rauh and Sufi, 2010). This assumption may also arise from a bank's dividend adjustment costs, or its risk aversion (Adrian and Shin, 2011).

An important caveat within these modeling restrictions is the inability for interest rates r_b and r_m to adjust in equilibrium. This arises from the restriction on both supply of deposits to banks, along with assumed liquidity and size of the corporate bond market. The quantity of bank loans and market debt are each assumed to be infinitely elastic at their respective (fixed), "equilibrium" interest rates. Nonetheless, there is generally a finite amount of financing banks can offer, which may arise from balance-sheet constraints. Differently, market-based lending is generally more elastic, due to the sheer number of public creditors willing to hold firms' corporate debts. In both cases, infinitely elastic quantities may be unrealistic. Still, these restrictions are reasonable when focusing on the cross-sectional relationship between variable markups and debt structures, which is this chapter's main focus.

Firm Entry

Firm entry is exogenous, and modeled so the mass of exiting firms in liquidation is replaced by an identical mass of entrants. Thus, the firm entry rate, denoted by Ω, is equal to the exit rate. This simplification ensures the total mass of active firms always remains constant, and can therefore be normalized to one, resembling the entrant dynamics in Luttmer (2007) and Gabaix et al. (2016).[19]

Every period, entrant firms are characterized by states (μ, k, b, m, z), which are drawn from the joint, generalized Pareto entry distribution $\boldsymbol{\Upsilon}$, i.e. $(\mu, k, b, m, z) \sim \boldsymbol{\Upsilon}(\mu, k, b, m, z)$. $\boldsymbol{\Upsilon}$ is independent in each state:

$$\boldsymbol{\Upsilon}(\mu, k, b, m, z) = Par(\mu; \xi_\mu, \sigma_\mu)\, Par(k; \xi_k, \sigma_k)\, Par(b; \xi_b, \sigma_b) \tag{1.22}$$

$$\times\, Par(m; \xi_m, \sigma_m)\, Par(z; \xi_z, \sigma_z) \tag{1.23}$$

with parameters (ξ_s, σ_s) denoting the "shape" and "scale" of the marginal, generalized Pareto distributions of each state $s \in \{\mu, k, b, m, z\}$. The state-space $\mathcal{S}$ will be a five-dimensional compact space. By modeling entry with generalized Pareto distributions, I match power-law type behavior observed in the distributions of those real-world counterparts to each of my model's five state variables. I defer discussion of how I calibrate the "shape" and "scale" parameters to **Appendix A.5**.

It is worth mentioning the support of $\boldsymbol{\Upsilon}$ is restricted so firms do not immediately exit again after entering. This implies entrants cannot take large, outstanding positions in both bank and market debt, forcing them to immediately liquidate after going public. At birth, firms must also have a sufficiently large customer base and capital stock to initiate business. This restriction is consistent with the model by Begenau and Salomao (2016), in which entry

[19]Incorporating firm entry is also crucial for generating a stationary distribution absent of survivorship bias.

is restricted to prevent firms from immediately borrowing large levels of debt, paying out dividends, and liquidating.[20]

Given firms' optimal policies, along with the restriction on firm entry and exit, the law of motion for the (joint) distribution of firms on $\mathcal{S}$ can be written as

$$\mathbf{G}'(\mu, k, b, m, z) = M(\mathbf{G}(\mu, k, b, m, z))$$

with $M : \Psi(\mathcal{S}) \to \Psi(\mathcal{S})$ representing the transition mapping over firm measures, and $\Psi(\mathcal{S})$ denoting the set of measures on $\mathcal{S}$ that are absolutely continuous with respect to the Lebesgue measure.

Stationary Equilibrium

Given an initial firm distribution, a *recursive, stationary equilibrium* consists of (i) the value function $\mathbf{V}(\mu, k, b, m, z)$, (ii) policy functions $i(\mu, k, b, m, z)$, $p(\mu, k, b, m, z)$, $l_b(\mu, k, b, m, z)$, and $l_m(\mu, k, b, m, z)$, (iii) lending rates r_b and r_m, as well as lending functions D_b and D_m, (iv) the entry/exit rate Ω, (v) the joint entry distribution $\mathbf{\Upsilon}$, and (vi) the measure $\mathbf{G}$ of firms that move along the state-space $\mathcal{S}$ according to the transition mapping M, such that:

1. The value function $\mathbf{V}(\mu, k, b, m, z)$, and policy functions $i(\mu, k, b, m, z)$, $p(\mu, k, b, m, z)$, $l_b(\mu, k, b, m, z)$, $l_m(\mu, k, b, m, z)$ of *active* firms solve the problem given by (1.13);

2. Equilibrium lending rates satisfy (1.21);

3. Equilibrium lending terms satisfy the zero-profit conditions of lenders given by (1.19) and (1.20);

4. The transition mapping M is consistent with firms' optimal policies, the exit/entry rate Ω, and the joint entry distribution $\mathbf{\Upsilon}$ given by (1.22).

5. The joint distribution $\mathbf{G}$ of firms is invariant, and has a fixed point.

The existence and uniqueness of a recursive, stationary equilibrium can be proved by adapting the same mathematical arguments used in Crouzet (2017). Standard approaches, such as those employed in Cooley and Quadrini (2001), cannot be directly applied here for the same two reasons noted in Crouzet (2017). First, since my problem features a discrete choice between liquidation, bank debt restructuring, and normal debt repayment, the value function $\mathbf{V}$ in (1.13) has kinks, and not globally concave. Second, for each $(\mu, k, b, m, z) \in \mathcal{S}$, the set of feasible contracts will not be convex.

By adapting the proof of Proposition 3 in Crouzet (2017), it can be shown that the firm's problem has a unique solution, and there exists a unique, steady-state distribution of firms across states (μ, k, b, m, z). The latter set of derivations draw from standard approaches,

[20] The authors also note that in Compustat data, immediate liquidation is not observed across public U.S. firms.

such as those in Stokey et al. (1989), which are sufficient to prove the transition mapping M has a fixed point.[21]

Lastly, the recursive stationary equilibrium cannot be obtained in closed-form. I will resort to numerical methods, which I discuss in **Section 1.5.3**.

1.5.2 Parametrization and Calibration Strategy

To compare model performance to my empirical findings, the model is parametrized and calibrated at an annual frequency. Parameters are divided into two categories. The first category consists of standard parameters taken directly from past works. The second category consists of parameters that I calibrate to target relevant moments in a sub-sample of firms studied in **Section 1.4**. Instead of using the full sample from 1992 to 2016, I only use information until 2007. I do this for the sake of using my model to predict the response of variable markups to a bank credit supply shock, akin to the one experienced during the 2008-09 financial crisis. This is carried out in **Section 1.7**.

Table 1.8 summarizes the values for parameters in both categories. The annualized risk-free rate r is set to 3%, in accordance with the estimate in Dou and Ji (2017). The elasticity of demand η is set to 1.5 following Backus et al. (1994). The capital depreciation rate δ is set to 0.15, in line with estimates from Hennessy and Whited (2007). I set the corporate marginal tax rate τ_c to 31%, and the interest income marginal tax rate τ_d to 29.6%, in accordance with estimates from Graham (2000). The recovery value χ is set to 0.60. This value is the median pre- to post-bankruptcy estimated change in asset values for the set of firms analyzed in Bris et al. (2006).[22]

Proxies for market- and bank-specific intermediation costs, γ_m and γ_b, closely follow estimates in Crouzet (2017). The market-specific cost γ_m is set to 0.01, or 1%. It is consistent with recent estimates of underwriting fees for corporate bond issuances (Altınkılıç and Hansen, 2000; Fang, 2005). Following Crouzet (2017), the bank-specific cost γ_b is constructed indirectly, by matching the 2007 average bank debt share in my sample. The bank debt share in 2007 was, on average, 49.9% for public U.S. firms in both CIQ and Compustat. In my model, this is consistent with $\gamma_b = 0.025$, or 2.5%, and greater than the value of 1.74% used in Crouzet (2017), which he obtains by calibrating his model to a bank debt share of 24% for medium and large U.S. manufacturing firms in 2007Q3.

I now describe the second set of parameters. The variable factor price w is calibrated to match the average estimated variable markup from 1992 to 2007, which is 1.337. This sample statistic is close to the observable, average markup of 1.36 over a full sample period (see Row 1 of **Table 1.5**). The parameter governing customer base growth, γ, is set to 0.18. This value is chosen as close as possible, to match the "peak" market debt share at 61%

[21] The technicalities arising in discrete time from my discrete choice setup are handled with much greater ease when working in continuous time. This is another motivation for numerically solving my model using a continuous-time formulation. This is discussed in **Section 1.5.3**.

[22] The median estimate is adjusted for the value of collateralized assets, which creditors may have recuperated outside of any formal bankruptcy arrangements.

of the hump shape between markups and market debt shares estimated from 1992 to 2007 (Column (1) of **Table A.2**).

Parameters, α, z_1, z_2, λ_1, and λ_2, which govern the elasticity of variable factor v, as well as the dynamics of idiosyncratic risk z, are calibrated with output from the method used to estimate markups. An outline of this procedure is deferred to **Appendix A.5**.

Because it governs volatility of investment, I choose capital adjustment cost parameter a to closely match the sample standard deviation of capital expenditures over assets, which is 0.0637 from 1992 to 2007. The parameter directly related to bank and market debt issuance costs, ϕ, is chosen in a similar manner. I set ϕ to closely match the sample standard deviation of leverage, which is 0.273.

It is worth mentioning the stability of those sample statistics chosen to calibrate parameters a and ϕ. The sample standard deviations in capital expenditures over assets and leverage from 1992 to 2016 are 0.0633 and 0.262, respectively (see **Table 1.5**). These values are comparable to statistics calculated for the period ending in 2007.

1.5.3 Numerical Solution Method

To solve numerically, I recast my model in continuous time. This allows me to exploit efficient methods introduced in Achdou et al. (2017), and recently implemented in Kaplan et al. (2018).[23]

I do this by recasting my discrete-time model as a continuous-time, "mean-field game" following Lasry and Lions (2007) and Achdou et al. (2017). This boils down to summarizing both the evolution of the value function in my Bellman equation and the stationary distribution with two coupled structures: a Hamilton-Jacobi-Bellman Variational Inequality (HJBVI), and a Kolmogorov Forward equation (KFE). The HJBVI is a Hamilton-Jacobi-Bellman (HJB) equation that easily handles non-convex, optimal decision rules. Specifically, those associated with my formulation of liquidation, bank debt restructuring, and normal debt repayment.[24] The Kolmogorov Forward equation governs the transition dynamics of the stationary distribution. The HJBVI runs backwards and looks forward, while the KFE runs forward and looks backwards. This coupled system fully characterizes the existence and uniqueness of my model's stationary equilibrium (Bertucci, 2017).

In addition to easily handling non-convexities relative to traditional, discrete-time methods, the "mean-field game" formulation provides other advantages. First, a "sparsity" arises when solving my discretized versions of both the HJBVI and the law of motion for the stationary distribution. Since their respective solutions involve solving extremely sparse systems of linear equations, convergence is achieved in a significantly shorter time frame. Second,

[23] In moving from discrete to continuous time, it is worth noting the maturity of both debt instruments becomes vanishingly small, in a manner similar to Abel (2018). This is equivalent to postulating instantaneously maturing debt. However, my model can be generalized to enable firms to issue multi-period or perpetual debt. The former can be modeled using the exponential decay framework of Leland, 1994a; Leland, 1994

[24] The HJB equation is a continuous-time analog of the Bellman equation in discrete-time.

because there is a tight, mathematical link between solving the HJBVI and the KFE, and having computed the solution to the HJBVI, the KFE's solution is obtained for free as the transpose of an adjusted matrix corresponding to the HJBVI's solution.

Equipped with my continuous-time formulation, I implement a variant of the "upwind, finite-difference scheme (FDS)" presented in Achdou et al. (2017). This scheme produces numerical solutions in short time, whilst being transparent, relatively easy to implement, and grounded in well-developed mathematical theory (Barles and Souganidis, 1991). The formulation of the continuous-time model, along with the numerical algorithm, are found in the **Online Appendix**.

1.6 The Model's Performance and Hump-Shaped Structure

In this section, I describe my calibrated model's main quantitative findings. First, I summarize its basic properties by reporting key un-targeted, cross-sectional averages of firm characteristics. Second, I report unconditional medians and standard deviations of major aggregate ratios. Third, I compare the model-implied and empirical, hump-shaped structures between variable markups and market debt shares. I conclude by touching on the role of idiosyncratic productivity in the hump shape.

Basic Properties

Table 1.9 presents the results of the calibration exercise in terms of un-targeted cross-sectional averages of major firm characteristics. I split both the empirical and model-implied distribution of firms into tertiles based on asset size. My calibration yields a tight, qualitative match between the model and the data along these dimensions. Notably, my model captures the empirical, cross-sectional patterns of the variable markup $\mathcal{M}$, market debt share $MarketDebtShare$, as well as the profitability ratio.

My calibration generates variable markups increasing in size, consistent with my sample and the findings in Traina (2018). Larger firms have larger market debt shares, which is line with prior, empirical results in the literature, as well as theoretical predictions in Crouzet (2017) and Xiao (2018).

Albeit, a firm's credit quality is not featured in my model, to the extent asset size and credit quality are positively correlated, my model is consistent with the studies in Denis and Mihov (2003), Rauh and Sufi (2010), and Colla et al. (2013). I also capture the cross-sectional patterns of profitability (defined as sales over total assets). In particular, larger firms are less profitable than smaller firms, as a result of diminishing returns to employing more capital to generate sales.

Table 1.10 reports both the un-targeted median and standard deviation of the average variable markup, leverage ratio, and market debt share. My calibration produces a tight, quantitative match between the model and data. Not only does my model indirectly match the average medians of these three aggregates, the model also generates volatilities similar to those observed in actual data.

The Model-Implied $\mathcal{M} - MarketDebtShare$ Relationship

The key finding in **Section 1.4** is the non-linear, hump-shaped relationship between public U.S. firms' variable markups and their market debt shares. As a result, I validate my calibration by assessing the model's ability to quantitatively match the observable, hump-shaped structure from 1992 to 2007. To compare my model to the data along this distinctive feature, I start by estimating the model-implied counterpart to specification (1.1). I do this by using the cross-section of firms generated by the model after solving for the stationary equilibrium. Pointedly, I estimate the density-weighted, quadratic regression specification:[25]

$$\begin{aligned}\mathcal{M} = \beta_0 + \beta_1 MarketDebtShare + \beta_2 MarketDebtShare^2 \\ + \beta_3 Leverage + \beta_4 SGAX + \epsilon\end{aligned} \tag{1.24}$$

I then repeat the core set of procedures from **Section 1.4**. My model generates estimates of β_1, β_2, and "peak" market debt share $\frac{\beta_1}{2\beta_2}$, each statistically different from zero at the 1% level. Panel (A) of **Figure 1.5** presents the estimated, non-parametric binned scatterplot, as well as the quadratic regression estimates associated with specification (1.24). The model-implied, hump-shaped structure is statistically different from zero and exhibits a "peak" share of 60.8%. This value is comparable to the empirical estimate of 61%.

Stark similarities in both the model-implied and empirical hump-shaped structures become self-evident in Panel (B). I plot the estimated, structural relationship for the mean *Leverage* and *SGAX* ratios in both the model and empirical distribution of firms. The "peak" of the quadratic relationship implied by the model is indistinguishable from the one estimated in my sample. This is expected, given my calibration strategy. Most importantly, my model's ability to generate a quadratic structure nearly identical to the one in the data, and across *all* market debt shares, both statistically and economically, is a true testament of the model's success. At the 5% significance level, the *difference* in estimated markups across all market debt shares is not statistically different from zero.

To further assess the validity of my model, I sort firms based on leverage ratio quartiles. Estimating the density-weighted, model-implied analog of specification (1.2),

$$\mathcal{M}_k = \beta_0 + \beta_1 MarketDebtShare_k + \beta_2 MarketDebtShare_k^2 + \varrho SGAX_k + u_k \tag{1.25}$$

[25]The regression is density-weighted, because (by definition) the steady-state distribution of firms obtained from my model provides firm observations with a different probability of being sampled. Also, as stated in **Section 1.5.1**, $\mathcal{M} \equiv \frac{p}{c(p)}$ and $SGAX \equiv \frac{\mu}{Sales}$, with $Sales \equiv \mu p^{1-\eta}$. The market debt share ($MarketDebtShare$) is given by $\frac{m}{(b+m)}$, whilst the leverage ratio ($Leverage$) is defined as the sum of bank and market debt over the capital stock, $\frac{(b+m)}{k}$.

with k = {low leverage, high leverage}, I find the model only generates a hump-shaped structure for highly-leveraged firms. This is conferred in Columns (2) and (3) of **Table 1.11**, even if the model-implied, "peak" market debt share is larger than found in the data. This may result from the model-implied quartiles not coinciding with those in the data. Particularly, because I only target the standard deviation of leverage in my calibration. Thus, higher moments, such as skewness and kurtosis, are unrestricted. Nonetheless, my model is consistent with the notion that firms place more weight on raising current profits at the expense of future losses in customers, whilst accumulating debt as their debt structures tilt more towards non-renegotiable market debt.

Lastly, I compare firms across customer base by splitting them at the median $SGAX$ ratio, similar to what I implemented in **Section 1.4**. I then consider the density-weighted, model-implied version of specification (1.3),

$$\mathcal{M}_k = \beta_0 + \beta_1 MarketDebtShare_k + \beta_2 MarketDebtShare_k^2 + \xi Leverage_k + v_k \qquad (1.26)$$

with k = {below median, above median}. Columns (4) and (5) of **Table 1.11** provide similar results to those shown in the empirical analysis. My calibration generates "peak" shares in the hump shape's of both low- and high-$SGAX$ firms sufficiently close to those in the data. Comparing columns (4) and (5) in **Tables A.2** and **1.11**, the model generates an optimal market debt share of 55.8% for low-$SGAX$ firms, which is slightly lower than the empirical "peak" of 59.8%. My model also predicts a "peak" share of 67% for high-$SGAX$ firms. This is marginally lower than the "peak" of 69.5% found in the data. Still, my calibration predicts a lower "peak" market debt share for firms below the median $SGAX$ ratio in comparison to firms above the median.

The upward-sloping portion of this hump-shaped structure results from positive benefits in boosting current profits via higher markups. This is done to offset an increasingly rigid debt structure. As a result, firms place less weight on future losses in customers.

The equilibrium market debt share determining the point at which these benefits are maximized is relatively *lower* if a firm's customer base is already low. If a firm currently has few customers, raising its markup today could result in no customers to sell to tomorrow. Regardless of its debt structure, this firm must rebuild demand by cutting its markup. Thus, at a low customer base, the benefits of a high markup diminish much faster, relative to the costs. The downward-sloping portion of this hump shape emerges at a relatively *lower* "peak" share. Overall, my model explains the empirical findings in **Section 1.4**, and is consistent with the two economic channels emphasized throughout this chapter.

The Role of Productivity in the Hump-Shaped Structure

The only source of uncertainty in the model is idiosyncratic productivity z, which is highly persistent. The expression for marginal costs c entering equation (1.10) indicates high-productivity firms face *lower* marginal costs in comparison to low-productivity firms. What remains unclear is the relationship between productivity and variable markups $\mathcal{M}$. In particular, how do differences in productivity affect the hump-shaped structure between markups and the market debt share? **Figure 1.6** compares the estimated structure of the hump shape for low- and high-productivity firms after estimating specification (1.24) and evaluating both *Leverage* and *SGAX* at their mean values for each group. Low-productivity firms ($z_{low} = 0.7962$) have both higher markups and a larger "peak" share in comparison to high-productivity firms ($z_{low} = 1.256$). This prediction is borne out by the data (see **Figure A.10** in **Appendix A.1**).

A firm with low productivity faces a higher likelihood of being forced into liquidation, by comparison. Despite its customer base, or leverage ratio, low-productivity firms will, on average, place less weight on future benefits of maintaining their locked-in customers and attracting new ones. As result, low-productivity firms will be more incentivized today to boost both operating profits and increased reliance on market debt, by setting a higher markup. As in the case with highly-leveraged firms, low-productivity firms will exhibit a higher "peak" market debt share in comparison to high-productivity firms. Because they have to exploit their locked-in customers more to continue operating, low-productivity firms have both relatively higher markups and "peak" market debt shares.

1.7 Aggregate Shocks and Counterfactuals

I now use the model to explore aggregate effects of a decline in bank credit supply. My experiment aims to replicate the bank credit crunch that occurred in the U.S. following the collapse of Lehman Brothers in September 2008. In particular, I study the perfect foresight response of firms to a one-time, exogenous shock to the intermediation wedge between bank and market credit, $\gamma_b - \gamma_m$. This occurs through a permanent increase in parameter γ_b, whilst holding γ_m fixed in steady-state.

I implement this experiment by matching the shift in the average market debt share within my sample of firms, which rose from 50.1% in 2007 to 52.9% in 2010. This 2.8 percentage point increase in the average share is replicated by my model with a corresponding increase in γ_b from 2.5%, to 5%. This is equivalent to an increase in the bank interest rate from 5.5% to 8%, implying an increase in the wedge from $\gamma_b - \gamma_m = 0.025 - 0.01 = 0.015$, or 1.5% to $\gamma_b - \gamma_m = 0.05 - 0.01 = 0.04$, or 4%.

Figure 1.7 compares the average and "peak" market debt shares of various hump-shaped structures, each corresponding to a bank-specific interest rate r_b. Interest rates r_b corresponding to the 2007-2010 average $MarketDebtShare$s are included in this figure. Each point on both the red and blue curves corresponds to a unique, steady-state, stationary equilibrium.

This figure highlights the response of firms to a contraction in bank credit akin to the one experienced in the U.S. during the most recent crisis. The "peak," or optimal market debt share, jumps from 60.8% at $r_b = 5.5\%$ to about 65.1% at $r_b = 8\%$. On average, the *equilibrium* market debt share determining the point at which the benefit of generating internal financing via higher markups is maximized, now transpires at a share 4.3 percentage points higher than before. This occurs because most firms substitute bank loans for non-renegotiable market debt (i.e. the median $MarketDebtShare$ increases from 50.3% to 52.3%), while their debt structures are less flexible. Thus, the majority of firms are exposed to more liquidation risk. The bank credit crunch changes the cross-sectional distribution of firms such that the average benefit in raising the markup to offset increased reliance on market debt grows. As a result, more firms place less weight on the future benefits of both new and locked-in customers.

This prediction is borne out by the data. In my sample, the median $MarketDebtShare$ also rises from 51.5% in 2007 to 56.2% in 2010, implying a greater majority of public U.S. firms tapped into market debt following the crisis. This is corroborated in works such as Becker and Ivashina (2014).

To some degree, this experiment also helps explain observable differences in firms' debt structures and markups around the crisis. Firms remaining below the "peak" of 65.1%, such as McDonald's, operated on the upward-sloping portion of this hump shape, whilst firms with shares above 65.1%, such as PepsiCo, found themselves on the downward-sloping part of this hump-shaped structure.

In response to the rise in spread $r_b - r_m$, the average markup $\mathcal{M}$ rises from 1.337 to 1.343, while total sales, my model's measure of aggregate output, declines from 3.005 to 2.751. Although this average variable markup is unweighted, the sales-weighted average $\mathcal{M}$ exhibits similar behavior.

The modest rise in my model's average variable markup, as well as the 8.5% drop in total sales, mirrors observed changes in my sample of public U.S. firms. The variable markup $\mathcal{M}$ rises from a 1992-2007 average of 1.337 to an average of 1.351 in 2010, while total sales fall by 11.8%. Thus, this aggregate shock accounts for almost 75% of the observed decline in total sales by public U.S. firms with access to both bank loans and market debt.

The behavior of both aggregates seems to suggest the markup is a-cyclical, considering its modest rise. However, without a general equilibrium framework, my model misses the *endogenous* decrease in spread $r_b - r_m$, arising from (expansionary) monetary policy aiming to stimulate firm output by reducing the risk-free rate r. Moreover, an endogenous reduction in overall consumption would constrain firms' abilities to manipulate variable markups following a contraction in bank credit. Thus, any aggregate results implied by my model may overstate the effects of a bank credit shock on the average variable markup *through* changes in firms' market debt reliance.

Counterfactual Analysis

Figure 1.7 also helps explore a counterfactual analysis. Having solved the model for various steady-states, I can focus on changes in steady-state equilibria beyond those associated with the U.S. from 2007 to 2010. I particularly explore how the hump shape's "peak" market debt share would have changed if the U.S. had experienced a bank credit shock smaller in magnitude to what was observed.

By comparing steady-states across a range of interest rates r_b, the figure shows the "peak" share exhibiting hump shape-like behavior. This "peak" is maximized at an interest rate r_b of 7.5%. If the U.S. had experienced a slightly less severe bank credit crunch, equivalent to an increase in r_b from 2.5% to 7.5%, then the "peak" $MarketDebtShare$ would have been at its highest. This implies the benefits of using internal financing to offset an increasingly rigid debt structure via markups, could have been sustained at a slightly larger market debt share of 65.8%.

I also consider a counterfactual "tax reform", whereby bank and market debt are not provided with the same tax advantage $\tau_d \in [0, 1]$. Specifically, I consider a tax structure in which market debt is given a higher tax advantage than bank debt, $\tau_d = \tau_b < \tau_m \in [0, 1]$. This amounts to modeling the perfect foresight response of firms to a one-time, exogenous shock in tax shield τ_m. This experiment affects the relative funding costs of bank and market debt.

By increasing its tax shield, market debt is marginally cheaper in the absence of either liquidation or bank debt restructuring. Even though market debt payments are still non-renegotiable, on the extensive margin, market debt liabilities are effectively lower. This reduces both liquidation losses and the potential need to generate internal financing via a higher markup. On the other hand, bank debt is now relatively costlier. Thus, this experiment is observationally equivalent to a small-scale bank credit supply shock.

I conduct this experiment by maintaining the calibrated interest tax rate at 29.6% for bank debt, though increasing the tax shield on market debt above 29.6%. **Figure 1.8** paints a similar picture to that of **Figure 1.7**. Starting at the steady-state in 2007, as τ_m increases relative to $\tau_d = \tau_b = 29.6\%$, the "peak" market debt share of the hump shape rises from 60.8% to about 63.5% at $\tau_m = 33.6\%$. This "peak" then declines. Declining behavior occurs for the same economic reasons as any case with a bank credit supply shock. The average market debt share also rises, before declining. The tax shield on market debt boosts market debt issuances of the average firm, because bank debt becomes relatively more expensive. Yet, the benefits of the tax shield eventually decline.

Both counterfactual exercises suggest aggregate shocks may shift the cross-sectional distribution of firms, such that more borrowing of market debt occurs in comparison to bank debt. This has essential implications for the cross-sectional distribution of variable markups. If the "peak" of this hump-shaped structure increases, then firms will find it more beneficial to set higher markups as a way of offsetting increased market debt issuances. Although some firms will be on the downward-sloping part of this hump shape, a greater "peak" share may result in more firms setting higher markups at the expense of loss in tomorrow's demand.

Overall, these counterfactual exercises explore the partial equilibrium effects of two aggregate shocks on both firms' debt structures and markup behaviors. Without a general equilibrium framework, my model is unable to address issues associated with the welfare implications of financial frictions, among other things.

1.8 Concluding Remarks

This chapter presents a theory explaining the observable hump-shaped relationship between a firm's variable markup and its market debt share. This hump shape is both novel and crucial for understanding how a firm's debt structure impacts its behavior in product markets. My dynamic model focuses on interactions between a customer market and the trade-offs in bank and market debt, generating the two channels analyzed throughout this chapter. Yet, my theoretical framework can be generalized along several dimensions.

First, a more general version of my model would explain households' decisions in a customer market with a micro-foundation. "Deep habits" (Ravn et al., 2006) may provide one avenue through which consumer preferences generate product market frictions, and this may enhance the "stickiness" of the customer base. Second, modeling the banking sector's various institutional frictions would enrich my model, helping me quantify the general equilibrium effects of a contraction in bank credit on firms' markup strategies.[26]

Empirical evidence suggests firms and banks form relationships (Chodorow-Reich, 2014). Theoretically, banking relationships result from asymmetric information (Diamond, 1991; Rajan, 1992; Holmstrom and Tirole, 1997). Asymmetric information models predict firms borrowing from banks with larger increases in their internal funding costs face a lower probability of obtaining a loan. Conditional on obtaining a loan, these firms also face greater borrowing costs. Extending my model along this dimension, by allowing a given firm to match to a specific bank, would provide a more realistic representation of how bank lending operates in practice.

While my model successfully replicates the empirically observed hump shape, it abstracts from complex yet important real-world features such as debt maturity structure, endogeneity of bank and market debt interest rates, as well as rich industry-level heterogeneity in market structure. Incorporating these and related features into my theoretical framework are essential for enriching any general equilibrium analysis.

Looking ahead, three meaningful yet unaddressed questions by this chapter are as follows: First, can monetary policy assist in stabilizing the adverse effects of a bank credit shock on firms' variable markups? Specifically, would introducing nominal rigidities, alongside a central bank, provide an automatic, stabilizing mechanism for dampening a widening intermediation wedge when the economy faces an aggregate contraction in bank credit? I leave this open to future research.

Second, what is the impact of endogenous firm entry on incumbent firms' debt structure choices and default risks? To the extent that increased competition alters the debt financing behavior of firms, in conjunction with their markup strategies, internal financing via adjustments in variable markups may be more limited, and the cost of bank debt may increase (Valta, 2012). Thus, endogenous firm dynamics may have first-order effects on the joint distribution of firms' debt financing and product pricing behaviors, translating to significant

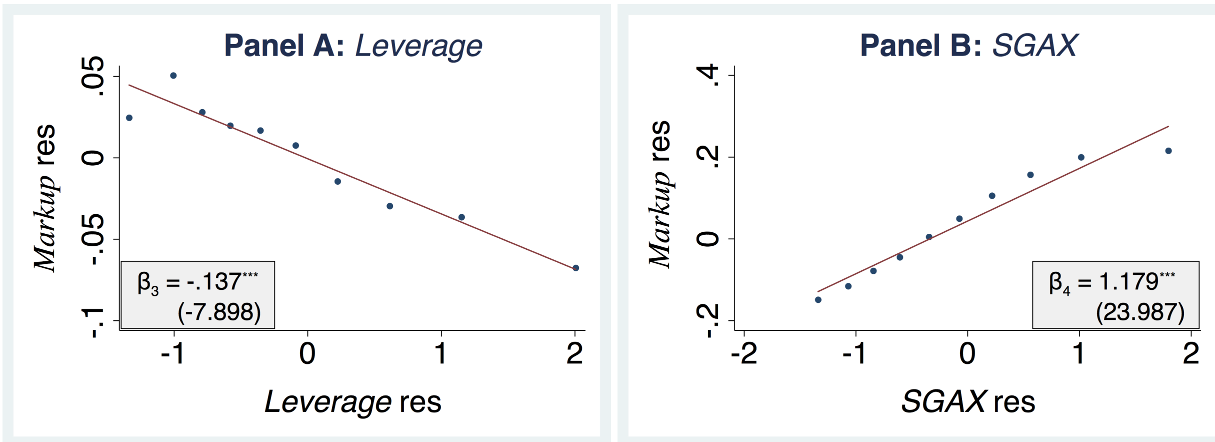
[26]Similar frictions are studied in the macro-banking model presented in Xiang (2017), who finds that a tightening of regulatory, capital requirements leads to a socially inefficient quantity of bank financing.

macroeconomic effects.

Third, what are the implications of my cross-sectional, non-linear structure between U.S. firms' markup behaviors and their debt borrowing choices for recent macroeconomic dynamics? In recent years, a debate centered on the rise in U.S. market concentration is at the core of both academic and policy discussions. Mirroring this trend is the surge in both corporate leverage and outstanding amounts of U.S. corporate market debt, raising some concerns about future prospects for U.S. economic growth.[27] My dissertation's first chapter is a building block in answering this question, and my next step will be expanding on my cross-sectional analysis to understand the aforementioned macroeconomic developments.

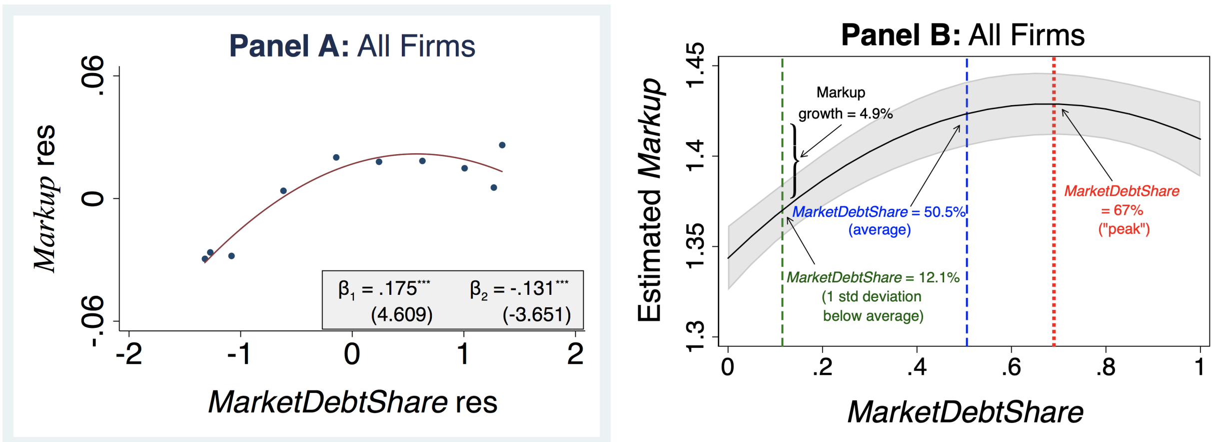
[27]One notable source: Nov. 21, 2018, "A $9 trillion corporate debt bomb is 'bubbling' in the US economy," CNBC.

Figure 1.1: Relationship between variable markup $\mathcal{M}$ and *Leverage*, *SGAX*



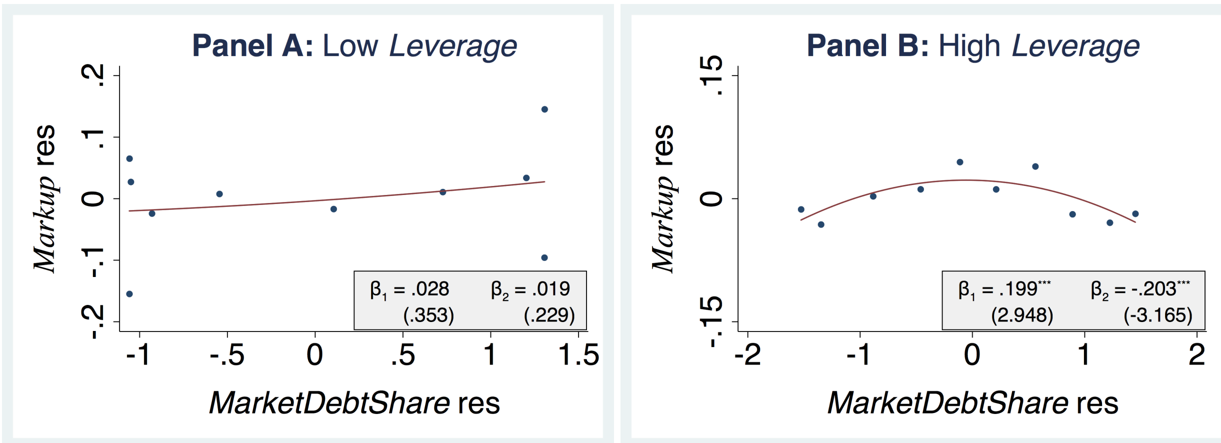
Note: This figure presents non-parametric estimates of conditional expectation functions (CEFs) using binned scatterplots, along with linear parametric estimates. In **Panel (A)**, the variable markup $\mathcal{M}$ and *Leverage* are residualized from $MarketDebtShare$, $MarketDebtShare^2$, and $SGAX$. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. *Leverage* is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. In **Panel (B)**, the variable markup $\mathcal{M}$ and $SGAX$ are residualized from $MarketDebtShare$, $MarketDebtShare^2$, and *Leverage*. *Leverage* and $SGAX$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best linear fit constructed using an OLS regression of $\mathcal{M}$ residuals on each respective set of "explanatory" residuals (*Leverage* or $SGAX$). In **Panel (A)**, the legend box (in **gray**) shows the point estimate for *Leverage* (β_3), while the legend box in **Panel (B)** shows the the point estimate for $SGAX$ (β_4), with t-statistics in parentheses. Standard errors are clustered by firm and year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1.2: Relationship between variable markup $\mathcal{M}$ and $MarketDebtShare$



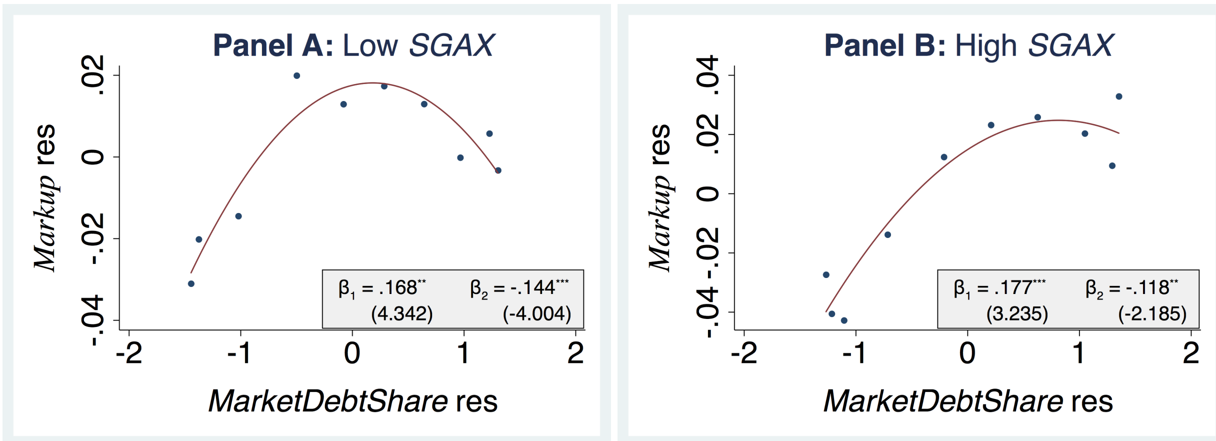
Note: **Panel (A)** presents a non-parametric estimate of the CEF using a binned scatterplot, along with a quadratic parametric estimate. The variable markup $\mathcal{M}$ and $MarketDebtShare$ are residualized from $Leverage$ and $SGAX$. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. $MarketDebtShare$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Panel (B)** presents the estimated quadratic, hump-shaped relationship between $\mathcal{M}$ and $MarketDebtShare$, with $Leverage$ and $SGAX$ evaluated at their mean values. The **gray** area represents 95% confidence intervals. In both panels, standard errors are clustered by firm and year.

Figure 1.3: Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $Leverage$



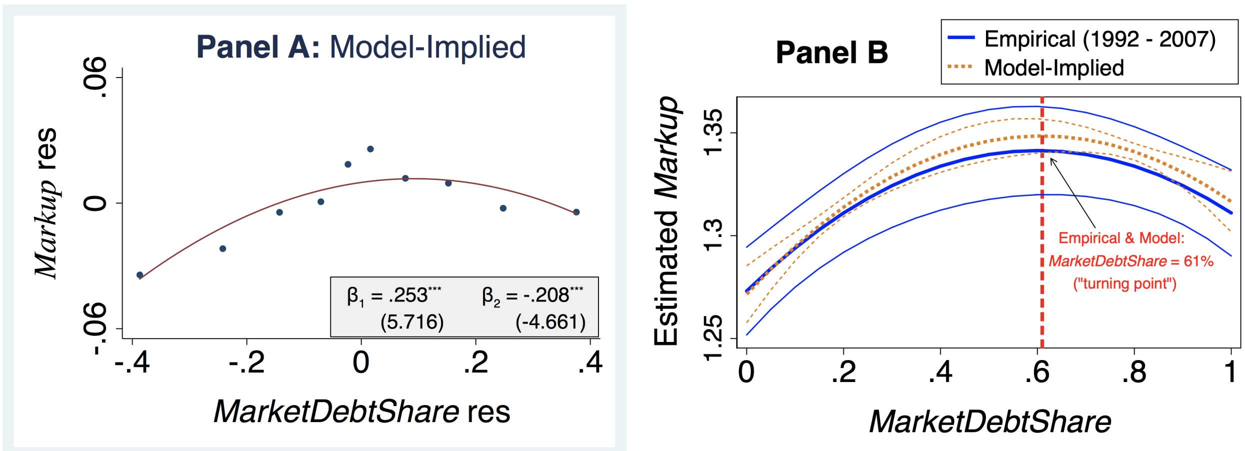
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. $Leverage$ is sorted into quartiles by year. The variable markup $\mathcal{M}$ and $MarketDebtShare$ are residualized from $SGAX$ for firms in the lowest (i.e. **Panel (A)**) and highest quartile (i.e. **Panel (B)**). The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. For each group, $MarketDebtShare$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals for each group. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1.4: Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SGAX$



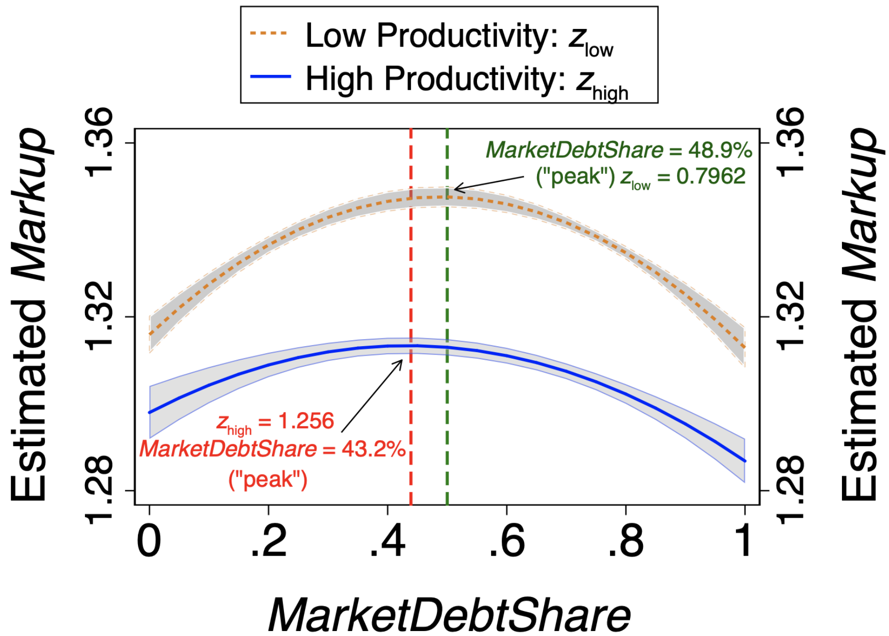
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. Firms are sorted into two groups based on their firm-level, time-series average $SGAX$ ratio. Firms below and above the median of this time-series average characterize the two separate groups. The variable markup $\mathcal{M}$ and $MarketDebtShare$ are residualized from $Leverage$ for firms below (i.e. **Panel (A)**) and above (i.e. **Panel (B)**) the median of this time-series average. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. For each group, $MarketDebtShare$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals for each group. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1.5: Model-Implied Relationship between $\mathcal{M}$ and $MarketDebtShare$



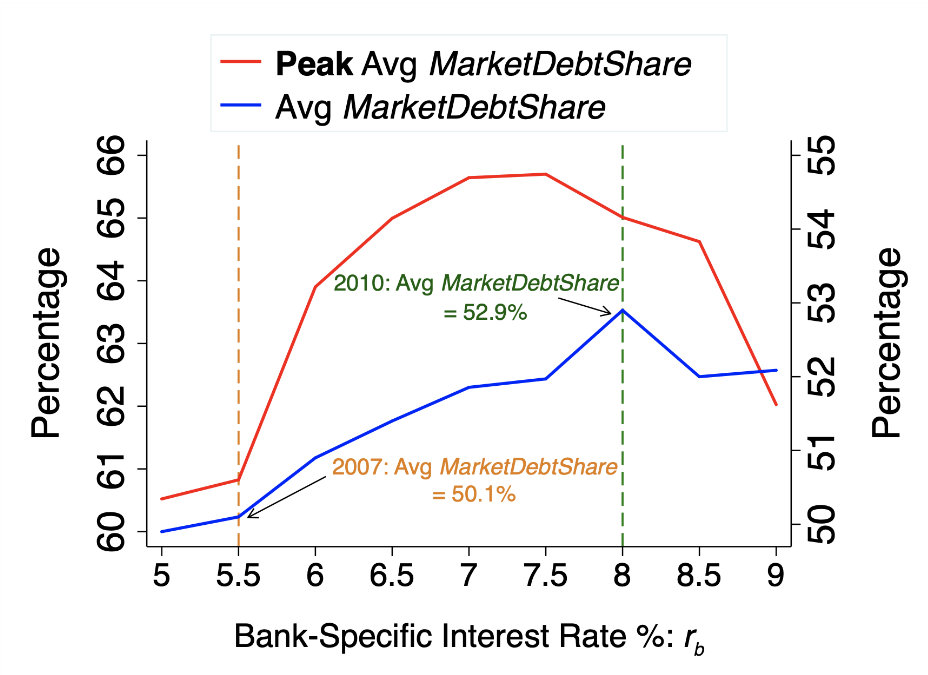
Note: **Panel (A)** presents a non-parametric estimate of the model-implied CEF using a binned scatterplot, along with a quadratic parametric estimate. The estimation using the model-implied analogs of $\mathcal{M}$, $MarketDebtShare$, $Leverage$, and $SGAX$ is conducted in the same manner described in the footnote to **Figure 1.2**. The variable markup $\mathcal{M}$ results from firms' static optimization of variable input v to production (see Equation 1.10). $MarketDebtShare$ is market debt m over the sum of bank and market debt, $(b+m)$. $Leverage$ is the sum of bank and market debt over the capital stock, $\frac{(b+m)}{k}$. $SGAX$ is the customer base over sales, $\frac{\mu}{Sales}$, with $Sales = \mu p^{1-\eta}$. As in **Figure 1.2**, the **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. **Panel (B)** compares the estimated model-implied and empirical hump-shaped relationships. Both $Leverage$ and $SGAX$ are included in the quadratic specification, and evaluated at their respective distributions' mean values. The solid **blue lines** around the (empirical) point estimate represent the 95% confidence interval band constructed by clustering on firm and year, while the dashed **orange lines** represent the model-implied 95% confidence interval band.

Figure 1.6: Model-Implied Relationship between $\mathcal{M}$ and $MarketDebtShare$ - (z_{low} vs. z_{high})



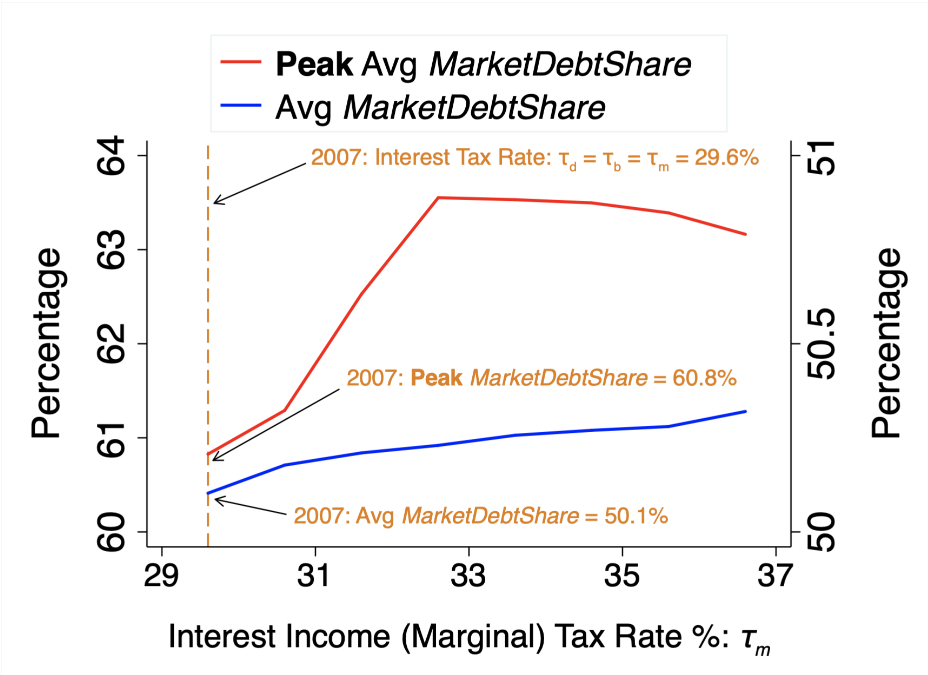
Note: This figure compares the estimated model-implied, hump-shaped relationship between $\mathcal{M}$ and $MarketDebtShare$ for low ($z_1 = z_{low} = 0.7962$) and high productivity firms ($z_2 = z_{high} = 1.256$). For each group, both $Leverage$ and $SGAX$ are included in the quadratic specification, and evaluated at their respective mean values based on the firm conditional distribution. The variable markup $\mathcal{M}$ results from firms' static optimization of variable input l to production (see **Equation 1.10**). $MarketDebtShare$ is market debt m over the sum of bank and market debt, $(b + m)$. $Leverage$ is the sum of bank and market debt over the capital stock, $\frac{(b+m)}{k}$. $SGAX$ is the customer base over sales, $\frac{\mu}{Sales}$, with $Sales = \mu p^{1-\eta}$. The solid **blue lines** and dashed **orange lines** around the point estimate for the set of z_{low} and z_{high} firms, respectively, represent 95% confidence interval bands around the model's point estimate.

Figure 1.7: Average and Hump Shape's "Peak" $MarketDebtShare$ across Bank Credit Shocks



Note: This figure compares the model-implied, average and "peak" $MarketDebtShare$s of various hump-shaped structures, each corresponding to a bank-specific interest rate r_b. $MarketDebtShare$ is market debt m over the sum of bank and market debt, $(b+m)$.

Figure 1.8: Average and Hump Shape's "Peak" $MarketDebtShare$ across "Tax Reform" Shocks



Note: This figure compares the model-implied, average and "peak" $MarketDebtShare$s of various hump-shaped structures, each corresponding to a market debt, interest income tax rate $\tau_m > \tau_b = \tau_d = 29.6\%$. $MarketDebtShare$ is market debt m over the sum of bank and market debt, $(b + m)$. The baseline case considered throughout this paper is given by $\tau_m = \tau_b = \tau_d = 29.6\%$.

Table 1.1: Contributed Data - Description of Variables

Variable	**Definition (and Item Codes)**	**References**
$FinCon$: Bodnaruk et al. (2015) text-based analysis measure of financial distress	percentage of "constraining" words in 10-K's; total number of "constraining" words divided by total words: $\frac{\sum[\mathrm{n}_{constraining}]}{\sum[\mathrm{n}_{words}]}$	Bodnaruk et al. (2015)

Table 1.2: CIQ - Description of Variables

Variable/Debt Instrument	**Definition (and Item Codes)**	**References**
CP: Commercial Paper	debt issue type [capitalstructuresubtypeid=1]	Colla et al. (2013)
DRC: Drawn Revolving Credit	debt issue type [capitalstructuresubtypeid $\in \{2, 9\}$]	Colla et al. (2013)
TL: Term Loans	debt issue type [capitalstructuresubtypeid=3]	Colla et al. (2013)
BN: Bonds and Notes	debt issue type [capitalstructuresubtypeid=4]	Colla et al. (2013)
CL: Capital Leases	debt issue type [capitalstructuresubtypeid=5]	Colla et al. (2013)
PT: Preferred Trusts	debt issue type [capitalstructuresubtypeid=6]	Colla et al. (2013)
OB: Other Borrowings	debt issue type [capitalstructuresubtypeid=7]	Colla et al. (2013)
$BankDebt$: Bank Debt	sum of DRC and TL	Xiao (2018)
$MarketDebt$: Market Debt	sum of CP and BN	Xiao (2018)
$MarketDebtShare$: Market Debt Share	$MarketDebt$ / ($BankDebt$ + $MarketDebt$)	Xiao (2018)

Table 1.3: Compustat and CRSP (Part A) - Description of Variables

Firm Characteristics	**Definition (and Annual/Q Item Codes)**	**References**
Size Measure #1: log(book assets)	Natural log of book assets, (2009 USD mill.) [#6(a), #44(q)]	Colla et al. (2013)
Size Measure #2: log(sales)	Natural log of sales, (2009 USD mill.) [#12(a), #2(q)]	Colla et al. (2013)
Firm Age (years)	Years since IPO, using first month a firm appears in CRSP	Colla et al. (2013)
Salesg: Sales growth (4q)	Simple annual growth rate of sales [#12(a), #2(q)]	
$SGAX$: SGA expenses-to-sales	Selling, general, and administrative expenses [#189(a), #1(q)] / sales [#12(a), #2(q)]	Gourio and Rudanko (2014)
ME: Market Value of Equity	Closing price [prc] $\times$ shares outstanding [shrout], (2009 USD mill.)	Davis et al. (2000)
BE: Book Value of Equity	BE is the book value of stockholder's equity [#216(a), #60(q)], plus balance sheet deferred taxes and investment tax credit (if available) [#35(a), #52(q)], minus the book value of preferred stock. Depending on availability, the redemption [#175(a), #71(q)], liquidation [#10(a)], or par value [#175(a), #71(q)] (in that order) is used to estimate the book value of preferred stock. Stockholder's equity is the value reported by Compustat, if available. If not, stockholder's equity is measured as the book value of common equity plus [#60(a), #59(q)] the par value of preferred stock, or the book value of assets [# 6(a), #44(q)] minus total liabilities [#181(a), #54(q)] (in that order), (2009 USD mill.)	Davis et al. (2000)
Leverage	($BankDebt$ + $MarketDebt$) / ($BankDebt$ + $MarketDebt$ + ME)	
Market-to-Book Assets	(ME + (Debt in current liabilities [#34(a), #45(q)] + long-term debt [#9(a), #51(q)]) + book value of preferred stock - balance sheet deferred taxes and investment tax credit [#35(a), #52(q)]) / book assets [#6(a), #44(q)]	Colla et al. (2013)
Cash Holdings: Cash-to-Book Assets	Cash and short-term investments [#1(a), #36(q)] / book assets [#6(a), #44(q)]	Bates et al. (2009), Xiao (2018)

Table 1.4: Compustat and CRSP (Part B) - Description of Variables

Firm Characteristics	**Definition (and Annual/Q Item Codes)**	**References**
Profitability	operating income before depreciation [#13(a), #21(q)] / book assets [#6(a), #44(q)]	Rauh and Sufi (2010)
Tangibility	(gross) property, plant, and equipment [#7(a), #118(q)] / book assets [#6(a), #44(q)]	Rauh and Sufi (2010)
Investment ratio	capital expenditures [#128(a), #90(q)] / book assets [#6(a), #44(q)]	Whited and Wu (2006)
Interest Rate Coverage ratio	(interest expense [#15(a), #22(q)] + income before extraordinary items [#18(a), #8(q)] + depreciation and amortization [#14(a), # 5(q)]) / interest expense [#15(a), #22(q)]	Ippolito et al. (2018)
Dividend Payouts	Annual sum of (common) cash dividends [#127(a), #89(q)], preferred dividends [#19(a), #24(q)], and purchase of common and preferred stock [#115(a), #93(q)] / book assets [#6(a), #44(q)]	based on Farre-Mensa and Ljungqvist (2016)
Dividend Payer Indicator: $\mathbb{1}\{DivPay > 0\}$	$Dummy = 1$ if Dividend Payouts are positive in the current year	
S&P Credit Rating	(Calendar) yearly average of the monthly S&P long-term issuer credit rating [splticrm] or S&P subordinated credit rating [spsdrm] if former is missing; [splticrm] and [spsdrm] are each assigned an integer value ranging from 1 ("AAA") to 23 ("NM")	based on Xiao (2018)
S&P Credit Rating Indicator: $\mathbb{1}_{\{\text{S\&P Credit Ratings} \geq 10\}}$	$Dummy = 1$ if firm has, on average, an investment grade credit rating, which is equivalent to "BBB-" and higher, i.e. S&P Credit Rating ≥ 10	
$INDSalesg$: Average Industry Sales Growth (4q)	Simple annual growth rate of total sales [#12(a), #2(q)] in 5-digit NAICS industries	
$Whited$-Wu (2006) Index	-0.091$\times$((income before extraordinary items [#18(a), #8(q)] + depreciation and amortization [#14(a), #5(q)]) / book assets [#6(a), #44(q)]) - (0.062$\times\mathbb{1}_{\{DivPay>0\}}$) + 0.021$\times$(long-term debt [#9(a), #51(q)] / book assets [#6(a), #44(q)]) - (0.044$\times$ log(book assets)) + (0.102$\times$ $INDSalesg$) - (0.035$\times$ $Salesg$)	based on Whited and Wu (2006), Hennessy and Whited (2007)

Table 1.5: Descriptive Statistics - Firm Characteristics (1992-2016)

	Mean	**SD**	**p5**	**p25**	**p50**	**p75**	**p95**	**N**
Markup $\mathcal{M}$ (COGS)	1.36	.295	.932	1.12	1.28	1.52	1.92	64,948
Markup $\mathcal{M}$ (COGS + SGA)	1.09	.135	.839	1.01	1.09	1.17	1.32	69,637
$MarketDebtShare$	.508	.381	0	.0843	.53	.899	1	32,124
$Leverage$	.33	.262	.000308	.113	.275	.502	.855	33,468
$SGAX$	.646	1.93	.0475	.142	.264	.456	1.73	93,024
log(book assets), (2009 USD mill.)	5.28	2.11	1.98	3.73	5.15	6.71	8.97	100,718
log(sales), (2009 USD mill.)	3.87	2.38	-.155	2.41	3.97	5.48	7.62	98,650
Firm Age (years)	14.9	13.5	.75	4.5	10.8	21.5	43.8	100,742
Investment ratio	.0538	.0633	.00295	.0154	.0335	.066	.18	99,603
Sales growth (4Q)	.2	.744	-.477	-.059	.0721	.246	1.12	91,924
Market-to-Book Assets	1.86	1.92	.453	.806	1.23	2.11	5.49	100,624
Cash-to-Book Assets	.208	.242	.00336	.0271	.104	.308	.766	100,714
Profitability	.00584	.0759	-.155	-.00368	.0255	.0439	.0814	99,611
Tangibility	.255	.229	.0179	.0765	.18	.369	.761	100,708
Interest Rate Coverage ratio	21.5	224	-103	-.148	4.61	14.8	195	84,717
Dividend Payouts	.0254	.0536	0	0	.00118	.0254	.13	87,443
$Whited$-Wu (2006) Index	-.225	.503	-.453	-.327	-.241	-.162	-.0506	90,885
Text-based Financial Constraints Index	.00685	.00207	.00365	.0054	.00674	.00813	.0105	87,441
S&P Credit Rating	A	3 ratings	AA	A+	A	BBB+	BB-	22,635
$\mathbb{1}_{\{\text{S\&P Credit Rating} \geq 10\}}$	.0869	.282	0	0	0	0	1	22,635

Note: Since accounting items sourced from CIQ, Compustat, and CRSP are in nominal levels, I deflate them using the GDP deflator indexed to 2009. Observations are winsorized at the 1^{st} and 99^{th} percentiles by year. $\mathcal{M}$ (COGS) denotes variable markups estimated with total variable costs given by Compustat's cost of goods sold (COGS), while $\mathcal{M}$ (COGS+SGA) denotes variable markups estimated with COGS plus SGA expenses as the measure of total variable costs.

Table 1.6: Regressions Associated with Binned Scatterplots - $\mathcal{M}$ and $MarketDebtShare$

<table>
<tr><th rowspan="2">VARIABLES</th><th colspan="5">Variable markup $\mathcal{M}$</th></tr>
<tr><th>(1) All Firms</th><th>(2) Low Leverage</th><th>(3) High Leverage</th><th>(4) Low SGAX</th><th>(5) High SGAX</th></tr>
<tr><td>$\widehat{\beta}_1$: $MarketDebtShare$</td><td>0.175***</td><td>0.028</td><td>0.199***</td><td>0.168***</td><td>0.177***</td></tr>
<tr><td></td><td>(4.609)</td><td>(0.353)</td><td>(2.948)</td><td>(4.342)</td><td>(3.235)</td></tr>
<tr><td>$\widehat{\beta}_2$: $MarketDebtShare^2$</td><td>-0.131***</td><td>0.019</td><td>-0.203***</td><td>-0.144***</td><td>-0.118**</td></tr>
<tr><td></td><td>(-3.651)</td><td>(0.229)</td><td>(-3.165)</td><td>(-4.004)</td><td>(-2.185)</td></tr>
<tr><td>“Peak” share : $\frac{\widehat{\beta}_1}{(2\times\widehat{\beta}_2)}$</td><td>.67***</td><td>-.756</td><td>.491***</td><td>.586***</td><td>.751***</td></tr>
<tr><td></td><td>(11.257)</td><td>(-.14)</td><td>(11.156)</td><td>(5.526)</td><td>(8.823)</td></tr>
<tr><td>Wald test of Equality in $\frac{\widehat{\beta}_1}{(2\times\widehat{\beta}_2)}$ χ^2 (p-value)</td><td></td><td colspan="2"></td><td colspan="2">4.65**
(0.031)</td></tr>
<tr><td>Firm Controls</td><td>No</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td>Industry FE</td><td>No</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td>Year FE</td><td>No</td><td>No</td><td>No</td><td>No</td><td>No</td></tr>
<tr><td>Observations</td><td>21,162</td><td>5,322</td><td>5,250</td><td>10,586</td><td>10,576</td></tr>
<tr><td>R^2</td><td>0.166</td><td>0.008</td><td>0.026</td><td>0.025</td><td>0.018</td></tr>
</table>

Note: This table presents regression estimates for the quadratic specifications associated with **Figures 1.2** through **1.4**. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. t-statistics of point estimates are in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.7: Examples of "Low" and "High" $SGAX$ Compustat Firms

"Low" average $SGAX$ Firms	Variable Markup $\mathcal{M}$				Firm-level $SGAX$ ratio				
	2002	**2007**	**2010**	**2015**	**2002**	**2007**	**2010**	**2015**	Avg **1992-2007**
American Airlines Group	**0.979**	**1.029**	**0.990**	**1.307**	0.129	0.122	0.127	0.169	0.089
McDonald's	**1.278**	**1.293**	**1.321**	**1.221**	0.125	0.115	0.107	0.106	0.115
Kroger Co.	**1.286**	**1.223**	**1.204**	**1.203**	0.206	0.184	0.189	0.173	0.186
YUM! Brands	**1.206**	**1.212**	**1.268**	**1.208**	0.128	0.152	0.147	0.160	0.136
"High" average $SGAX$ Firms	Variable Markup $\mathcal{M}$				Firm-level $SGAX$ ratio				
	2002	**2007**	**2010**	**2015**	**2002**	**2007**	**2010**	**2015**	Avg **1992-2007**
Alphabet (Google)	N/A	**1.067**	**1.186**	**1.185**	0.296	0.297	0.364	0.363	0.305
PepsiCo	**1.178**	**1.169**	**1.836**	**1.842**	0.315	0.381	0.400	0.413	0.407
Nike	**1.841**	**1.960**	**1.979**	**2.020**	0.302	0.303	0.331	0.333	0.301
New York Times Co.	**1.670**	**1.555**	**1.618**	**1.662**	0.327	0.405	0.411	0.404	0.407

Source: S&P's Compustat; Author's calculations.

Note: The industry classification is 5-digit NAICS. Firms with "low" and "high" $SGAX$ ratios are firms below and above the median firm-level, time-series average $SGAX$ ratio, respectively. This split is described in **Section 1.4**. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $SGAX$ is SGA expenses over sales.

Table 1.8: Parametrization and Calibration

	Parameter	**Description**	**Source**	**Data**	**Model**
Demand	$\eta = 1.5$	Elasticity of Demand	Backus et al. (1994)		
Customer Base	$\gamma = 0.18$	Customer base growth	Hump-shaped relationship's "peak" market debt share (1992-2007)	0.61	0.608
	$(1-\alpha) = 0.93$	Variable factor share	Avg industry variable factor elasticity v		
	$w = 0.36$	Varible factor price	Avg firm variable markup $\mathcal{M}$ (1992-2007)	1.337	1.337
	$z_1 = 0.7962$	"Low" productivity state	Avg firm $AR(1)$ parameters		
Production	$z_2 = 1.256$	"High" productivity state	Avg firm $AR(1)$ parameters		
	$\lambda_1 = 0.007$	"Low" productivity state rate	Avg firm $AR(1)$ parameters		
	$\lambda_2 = 0.007$	"High" productivity state rate	Avg firm $AR(1)$ parameters		
Capital	$a = 3.55$	Capital adjustment cost	Avg firm investment ratio $\frac{i}{k}$, (1992-2007)	0.0637	0.0667
	$\delta = 0.15$	Capital depreciation rate	Hennessy and Whited (2007)		
Taxes	$\tau_c = 0.310$	Corporate tax rate	Graham (2000)		
	$\tau_i = 0.296$	Interest income tax rate	Graham (2000)		
	$r = 0.03$	Risk-free rate	Dou and Ji (2017)		
	$\gamma_m = 0.010$	Market intermediation cost	Crouzet (2017)		
Financing Costs	$\gamma_b = 0.025$	Bank intermediation cost	based on Crouzet (2017), Avg $MarketDebtShare$ in 2007		
	$\chi = 0.60$	Liquidation deadweight loss	Bris et al. (2006)		
Capital Structure	$\phi = 1.2$	Debt issuance cost	Avg $Leverage$ $\frac{b+m}{k}$ (1992-2007)	0.273	0.282

Table 1.9: Un-targeted Cross-Sectional Averages from 1992 to 2007 - (Size Tertiles)

VARIABLE	$\leq 33\%$		$33\% - 66\%$		$\geq 66\%$	
	Data	Model	**Data**	Model	**Data**	Model
Variable Markup $\mathcal{M}$	1.315	1.286	1.327	1.331	1.341	1.399
$MarketDebtShare$	0.409	0.514	0.496	0.524	0.669	0.545
Profitability: $\frac{Sales}{Assets}$	0.327	1.193	0.297	0.376	0.255	0.271

Note: Variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt.

Table 1.10: Un-targeted Aggregate Moments from 1992 to 2007

VARIABLE	MEDIAN		STD DEVIATION	
	Data	Model	**Data**	Model
Variable Markup $\mathcal{M}$	1.283	1.284	0.295	0.245
$MarketDebtShare$	0.552	0.503	0.367	0.234
Leverage	0.338	0.282	(targeted)	(targeted)

Note: Variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. *Leverage* is the sum of bank and market debt over the market value of assets.

Table 1.11: Model-Implied Regressions - $\mathcal{M}$ and $MarketDebtShare$

VARIABLES	**Variable markup $\mathcal{M}$**				
	(1) **All *Firms***	(2) Low *Leverage*	(3) **High *Leverage***	(4) **Low *SGAX***	(5) **High *SGAX***
$\widehat{\beta_1}$: $MarketDebtShare$	0.253***	-0.119	0.361***	0.095***	0.490***
	(5.716)	(-1.265)	(12.060)	(6.310)	(4.300)
$\widehat{\beta_2}$: $MarketDebtShare^2$	-0.208***	0.118	-0.227***	-0.085***	-0.366***
	(-4.661)	(1.366)	(-7.386)	(-5.952)	(-3.242)
"Peak" share : $\frac{\widehat{\beta_1}}{(2\times\widehat{\beta_2})}$	**.608***	503	**.796***	**.558***	**.67***
	(22.171)	(1.582)	(17.036)	(24.957)	(12.259)
Wald test of Equality in $\frac{\widehat{\beta_1}}{(2\times\widehat{\beta_2})}$				4.37**	
χ^2 (p-value)				(0.046)	
Firms/Observations	57,600	17,840	14,400	29,508	28,092
R^2	0.608	0.523	0.596	0.096	0.102

Note: This table provides model-implied, regression estimates associated with the quadratic specification presented in **Panel (A)** of **Figure 1.5**, as well as the model-implied versions of the quadratic specifications shown in Columns (2) through (5) of **Table 1.6**. The variable markup $\mathcal{M}$ results from firms' static optimization of variable input v to production (see Equation 1.10). $MarketDebtShare$ is market debt m over the sum of bank and market debt, $(b+m)$. $Leverage$ is the sum of bank and market debt over the capital stock, $\frac{(b+m)}{k}$. $SGAX$ is the customer base over sales, $\frac{\mu}{Sales}$, with $Sales = \mu p^{1-\eta}$. In the implementation of the numerical algorithm, I solve the model over a discretized 5-dimensional, state-space grid resulting in 57,600 grid points. t-statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 2

International Monetary Policy Spillovers: A High-Frequency Approach

2.1 Introduction

The subject of international monetary spillovers is at the core of recent policy discussions in both international macroeconomics and finance. A recent literature suggests monetary policy by the U.S. Federal Reserve is a fundamental driver of global asset prices, bank leverage, and the availability of credit (Rey et al., 2013; Miranda-Agrippino and Rey, 2015). This view has generated a debate on the nature of monetary policy's real spillovers, and whether a surprise monetary announcement made by the Federal Reserve propagates to both small and open economies, as well as to foreign emerging markets. For instance, the 2013 "Taper Tantrum" in which Ben Bernanke, then Federal Reserve Chairman, announced a tapering of central bank asset purchases, led to both a decline in equities and a rise in bond yields in emerging markets. This had ensuing, contractionary real effects on emerging markets.

This chapter attempts to identify both financial and real spillovers of monetary policy with use of high-frequency identification of monetary announcements from major central banks. Our approach uses changes in interest rate futures around scheduled monetary announcements as a measure of the *unanticipated* component of monetary policy. While high-frequency shocks have been used to identify asset price effects, they have low statistical power when used to identify their effects on a low-frequency variable, such as real gross domestic product (GDP). Identification is additionally difficult, considering a host of non-monetary factors affect real GDP in real-time. Most relevant critiques focus on whether monetary surprises at a high-frequency are useful in explaining low-frequency variables.

As a solution to the frequency mismatch between exogenous monetary surprises and real GDP, we make use of economic tracking portfolios (ETPs) recently implemented in Lamont (2001), Vassalou (2003), and Hébert and Schreger (2016). This method allows us to replicate real GDP growth with a set of base assets, including a country's equity, treasury and corporate bond indices, as well as relevant bilateral exchange rates. This portfolio of base asset returns has high explanatory power for real GDP growth, therefore replicating real GDP growth at a quarterly frequency. We use this portfolio of base assets to construct a high-frequency analogue of real GDP growth by utilizing information on base asset returns around monetary announcements. Taking the estimated, unconditional loadings of the tracking portfolio's base assets at a quarterly frequency, we construct a counterfactual change in real GDP growth around monetary announcements. We call this real GDP-tracking news.

Our constructed measure enables us to trace the impact of monetary surprises on real GDP growth. Adjusting the replicating portfolio's horizon enables us to trace and quantify the effects of monetary policy on real GDP-tracking news at different points in time. This provides an alternative to conventional impulse response functions when analyzing the long-run dynamics of a monetary shock on real GDP growth. Our assumed direction of causation rests on an exogenous monetary surprise affecting real GDP *through* movements in the set of base asset returns.

Primarily, our approach measures the effect of a monetary surprise by the U.S. Federal Reserve, as well as by the Reserve Bank of Australia and the Bank of Canada. To construct monetary surprises, we use changes in interest rate futures on the underlying central bank rate around scheduled monetary announcements to measure monetary news. The identifying assumption rests on changes in the futures rate responding, solely, to monetary news following announcements.

In addition to using interest rate futures on the underlying central bank rate, we exploit changes in treasury yields as an indicator of monetary policy's long-term stance. Longer-term measures are relevant in the present context, given that short-term futures have exhibited little change in countries affected by the zero lower bound (ZLB) in nominal interest rates. Measures of unconventional monetary policy implemented by the Federal Reserve, such as quantitative easing (QE), involved significant asset purchases of Treasury bonds which compressed long-term yields.[1] Therefore, following the methodology in Gurkaynak et al. (2004), we decompose monetary surprises into three components: *timing*, *level*, and *slope* components.

Timing and *level* components measure the short-term stance of monetary policy. *Timing* is a transitory surprise that leaves expected interest rates unchanged after the next FOMC announcement. The *level* component measures the change in interest rates typically at a three month horizon, and measures a parallel shift of interest rate expectations. The *slope* component is the residual change in long-term yields that is unexplained by the *timing* and *level* components. This component captures revisions to the expected pace of interest rate changes and the effects of unconventional monetary policy on the yield curve.

[1] Another example is the Federal Reserve's 2011 "Operation Twist" policy, which involved buying and selling government bonds in an effort to provide monetary easing for the U.S. economy. This policy was characterized by $400 billion (USD) purchases in bonds with maturities of 6 to 30 years, and sells in bonds with maturities less than 3 years. The policy's goal was targeting the long end of the yield curve, by compressing the difference between short- and long-term yields.

Equipped with this framework, we find changes in long-term interest rates, as measured by the *slope* component, lead to a contraction in real GDP-tracking news for Australia, Canada, and the United States. This holds for ETPs measured at various horizons, ranging from 1 to 12 quarters. This result is consistent with empirical work finding a decline in real GDP over the long-run, following a contractionary monetary announcement (Romer and Romer, 1989; Romer and Romer, 2004; Gertler and Karadi, 2015). Interestingly, our results are mostly driven by the *slope* component. This is intuitive, considering changes in longer-term yields are crucial determinants of the long-run, causal impact of monetary policy. For example, when an economy enters a recession, long-term yields fall as central banks pursue expansionary policies to bolster the economy out of said recession. In contrast, tightening of monetary policy in a boom period, due to concerns of high inflation, lead to higher long-term yields, which dampen a heating economy.

Our second key finding focuses on the effect of U.S. monetary policy on periphery countries, such as Australia and Canada.[2] Traditional models predict the effects of a U.S. monetary contraction lead to an exchange rate depreciation in a small, open economy with an expansion in net exports via expenditure switching effects. However, a recent literature on financial spillovers suggests a U.S. monetary contraction leads to a decline in global banking credit.[3] Our approach documents how a contractionary monetary surprise by the Federal Reserve leads to negative Australian real GDP-tracking news at most horizons. We find mixed results for Canada's real GDP-tracking news across different horizons.

While we offer a methodological contribution to identifying the causal effects of monetary policy, there are two major econometric concerns. First, we require the ETP to have sufficient explanatory power in replicating real GDP growth. To demonstrate the robustness of our replicating portfolio approach, we find the adjusted R^2 of our ETPs capture a significant fraction of the unconditional variation in real GDP growth. Furthermore, out-of-sampling fit tests indicate our replicating portfolios consistently outperforms a random walk at all horizons.

Second, the key econometric assumption made in our analysis is that the unconditional loadings of base assets in the ETPs are the same as the loadings conditional on a monetary shock. This assumption may be unrealistic if, for example, the base asset weights are of a different sign when the economy is hit by a series of non-monetary shocks, such as oil supply or technology shocks. Nonetheless, we take a crucial step toward providing both a new and refined method for identifying the international dimensions of the monetary transmission mechanism.

[2]Our choice of these countries as an analysis for spillovers results from the availability of high frequency data to accurately measure spillovers. It is documented in recent papers (Curcuru et al., 2018; Kearns et al., 2018) that U.S. monetary policy has significant effects on asset prices of these countries. In addition, both have high trade shares with the United States.

[3]An alternative theory of exchange rates, known as the "financial channel," suggests an appreciation of the U.S. dollar leads to an increase in U.S. dollar-denominated debt for banks in a foreign country borrowing in dollars. Thus, if banks are subject to regulatory leverage constraints, they reduce lending, which leads to contractionary real effects.

2.2 Related Literature

This chapter draws on extensive literature which uses high-frequency identification of monetary policy shocks (Kuttner, 2001; Gurkaynak et al., 2004, Bernanke and Kuttner, 2005; Gertler and Karadi, 2015; Nakamura and Steinsson, 2018). High-frequency identification methods rely on tick-by-tick interest rate futures data, coupled with an event-study approach for measuring changes in interest rate futures in a window around central bank announcements. While this approach is valid for measuring monetary surprises during periods of sufficiently positive interest rates, there is a concern about the method's validity when rates are near the ZLB. There is also a concern regarding whether the method captures the effects of unconventional monetary surprises, such as those arising from quantitative easing and forward guidance.

To quantify monetary surprises in the period of unconventional monetary policy, Gurkaynak et al. (2004) and Swanson (2015) examine the impact of monetary policy on asset prices using a factor structure. This methodology analyzes the response in a set of interest rate futures at different horizons, as well as treasury yields of varying maturity, to Federal Reserve announcements around a pre-specified intraday window. Using this variation, their measured first principal component is defined as a "target" factor, such as the Federal Funds rate. Their measured second principal component is called a "path" factor and quantifies the effects of both forward guidance and unconventional policy measures aimed at influencing longer-term rates.[4]

In this chapter, we implement an alternative method for capturing the effects of unconventional monetary policy. Specifically, we decompose changes in the term structure of interest rates using the method in Gurkaynak (2005). This approach rests on partitioning changes in both interest rate futures and treasury yields into a *timing*, *level*, and *slope* component. These components provide a measure for the stance of monetary policy at the short and long ends of the yield curve. With this method, we will infer the effects of surprises in monetary policy on a high-frequency measure of real GDP news.[5]

To construct real GDP news, we draw on Lamont (2001), Vassalou (2003), as well as Hébert and Schreger (2016). These papers provide a useful methodology for linking asset returns to news about macroeconomic fundamentals. We follow a methodology similar to Hébert and Schreger (2016). In their paper, they use high-frequency changes in default probabilities on Argentina's sovereign debt and find increases in these default probabilities lead to a decline in Argentinian asset returns. By constructing a portfolio that replicates real GDP, they are able to trace the effect of an exogenous rise in default probability on Argentina's real GDP growth. In this chapter, there is a clear parallel to their paper.

[4]For more details, we refer the reader to the methodology outlined in Swanson (2015). The principal components are effectively rotated so the first factor is perfectly correlated with the change in Federal Funds futures, while the second factor is orthogonal to changes in Federal Funds futures. Thus, the latter provides a measure of the effects of unconventional policies, such as QE and forward guidance.

[5]In contrast, using a factor approach to decompose interest rate surprises is difficult to interpret economically when examining the effect of the factors on macroeconomic indicators.

Specifically, we trace the macroeconomic effect of monetary surprises (in comparison to surprises in default probability) on real GDP growth through a portfolio of assets that "replicates" real GDP growth.

Our chapter also speaks to the literature on identifying the financial and macroeconomic effects of U.S. monetary policy, both domestically and across borders. High-frequency studies of FOMC announcements (Curcuru et al., 2018; Kearns et al., 2018) have identified significant cross-border effects of U.S. monetary policy on bond yields and stock indices. In particular, the aforementioned authors find that measures of the degree of trade and financial linkages with the U.S. can explain cross-country variation in response to U.S. monetary policy. We contribute to this strand of work by using asset returns around monetary announcements to identify an analogous high-frequency measure of real GDP growth.

In addition to financial spillovers, a series of papers use a structural vector autoregression (SVAR) approach to identify macroeconomic effects (Gertler and Karadi, 2015; Dedola et al., 2017; Bhattarai et al., 2015). For example, Gertler and Karadi (2015) first use high-frequency monetary shocks as an instrument for policy rate residuals in a traditional SVAR with financial variables. Based on their identification, they examine the effects of policy rate shocks on credit costs and real GDP growth. Using a similar SVAR approach, Dedola et al. (2017) find a contractionary monetary policy surprise in the U.S. results in a depreciation of most economies' currencies, a contraction in real GDP, as well as a decline in inflation, especially for advanced countries. Another notable example can be found in Bhattarai et al. (2015). These authors instrument for QE using balance sheet growth of the Federal Reserve following key FOMC announcements. In the period from 2008 to 2012, they find significant effects on asset prices of emerging markets in response to U.S. monetary easing.

The approaches taken in these and similar papers rely on the use of an SVAR, which requires restrictive assumptions about the timing of events. Using high-frequency monetary shocks in an SVAR also poses several problems. Most notably, using high-frequency monetary shocks as an instrument for the policy rate has relatively low power in predicting significant long-run responses of real GDP and other macroeconomic variables. We circumvent these and related issues by exploiting the fact monetary shocks at the high-frequency have relatively more power in explaining movements in asset returns. This variation can then be used to replicate real GDP growth.

This chapter is outlined as follows: **Section 2.3** introduces the methodology used for constructing a high-frequency measure of real GDP news via a "tracking" or replicating portfolio approach. In **Section 2.4**, we describe the data used to construct monetary policy surprises and the set of base assets used in our replicating portfolios. **Section 2.5** then presents our key findings. These findings include domestic policy effects on real GDP news, as well as macroeconomic spillover effects of Federal Reserve announcements on our measure of real GDP news for both Australia and Canada. Finally, **Section 2.6** concludes.

2.3 Methodology of Real GDP-Tracking Portfolios

We devise a method for identifying the effects of high-frequency monetary surprises on real GDP growth. In general, this is challenging because real GDP growth is observed at a low-frequency. While many studies find significant asset price effects around monetary announcements, high-frequency monetary surprises have low power for estimating effects of monetary policy on macroeconomic outcomes over long horizons.

Our method addresses this challenge by bridging the gap between both monetary policy and asset prices – both observed at a high frequency – and a low-frequency variable like real GDP growth. We operationalize this by implementing a simple two-step procedure. First, we replicate real GDP growth at a low-frequency using a large set of economically relevant base asset returns. We then examine the response of the replicating portfolio around monetary announcements to construct a measure of real GDP news at a high frequency. Secondly, we use our constructed measure of real GDP news via the replicating portfolios to infer the effects of monetary announcements on real GDP growth.

Constructing High-Frequency Real GDP-Tracking News

We define the return on a given base asset from time t to $t+k$ as $R_{i,t+k}$, and real GDP growth over the same period as Δy_{t+k}. Our base asset return, $R_{i,t+k}$, is a function of idiosyncratic news as well as systematic news, which includes the state of the economy. We capture the latter using the change in real GDP growth Δy_{t+k}, and other fundamentals, denoted by F_t.

$$R_{i,t+k} = \alpha_i \Delta y_{t+k} + \beta_i F_t + v_{i,t} \tag{2.1}$$

Here, $v_{i,t}$ represent an idiosyncratic disturbance. To the extent asset returns co-move with real GDP growth, we can use asset returns to construct a portfolio which replicates real GDP growth. We do so by regressing changes in real GDP over a horizon k on a set of concurrent base asset returns, which is given by (2.2). The key assumption for replication is that the portfolio of asset returns strongly co-moves with real GDP growth, $\rho(\widehat{\Delta y_{t+k}}, \Delta y_{t+k}) \approx 1$. To optimize the replicating portfolio, we use a wide range of base assets, comprising of exchange rates, stock and commodity indices, treasury yields, as well as corporate bond spreads:

$$\Delta y_{t+k} = \sum_{i=1}^{j} \gamma_{i,k} R_{i,t+k} + u_{t+k} \tag{2.2}$$

We use the loadings estimated in (2.2) and construct a counterfactual measure of real GDP news around monetary announcements. We first estimate actual changes in base asset returns around monetary announcements, which we denote by R_t^m. Using the predicted weights $\hat{\gamma}_1, \hat{\gamma}_2, ..., \hat{\gamma}_j$, we construct a high-frequency analogue of real GDP news, which we denote by $\widehat{\Delta y^m_{t+k}}$ (see (2.3)).

$$\widehat{\Delta y^m_{t+k}} = \sum_{i=1}^{j} \widehat{\gamma}_i R^m_{i,t} \tag{2.3}$$

Effects Of Monetary Surprises on Real GDP Growth

To infer the causal effects of monetary policy, we regress our measure of high-frequency real GDP news on measures of monetary surprises that span information across the term structure of interest rates (2.4). Following Gurkaynak (2005), we construct *timing*, *level*, and *slope* monetary surprises around scheduled monetary announcements. These components measure surprises at different horizons. *Level* represents monetary news at a medium-run horizon, *slope* represents monetary news at the long-end of the yield curve, and *timing* reflects the residual transitory news not captured in the *level* component.[6]

$$\widehat{\Delta y^m_{t+k}} = \Phi_1 timing_t + \Phi_2 level_t + \Phi_3 slope_t + u_{t+k} \tag{2.4}$$

We then measure the causal effect of these three monetary shocks on real GDP growth at different horizons. Decomposing interest rate responses in this manner helps capture the effects of the "term structure of monetary policy" on real GDP news. Moreover, it helps quantify the varying effects of unconventional policies during ZLB periods.

Finally, we use this methodology to examine spillover effects of U.S. monetary policy to periphery countries such as Australia and Canada. This entails first constructing real GDP-tracking news for both Australia and Canada using a set of domestic base asset returns around FOMC announcements. This object is then regressed on monetary surprises around FOMC announcements to infer the effect of U.S. monetary policy on the measured real GDP-tracking news of Australia and Canada.

Econometric Concerns

While we do offer a novel methodology for obtaining a counterfactual measure of real GDP growth at a high-frequency, there are some potential concerns. First, we assume the loadings $\{\gamma_i\}$ from (2.2) to be time-invariant. That is, we assume real GDP growth responds to asset returns with the same elasticity at an intra-day or quarterly frequency.

If firms base their decisions to hire or invest on market news at a low frequency, while stock traders respond to a monetary announcement for reasons orthogonal to long-term trends in a company (for example, due to speculation or herding motives), then estimated loadings constructed via the replicating portfolio may not be applicable at a high-frequency.

As a robustness test, **Section 2.5** demonstrates the adjusted R^2 of the GDP-tracking portfolio is sufficiently high such that our set of base assets capture significant unconditional

[6] For a more detailed description of how these three shocks are measured, we refer the reader to **Section 2.4**

variation in real GDP growth. Additionally, as a check of our estimates' stability, we test the out-of-sampling fit of our replicating portfolio by computing Root Mean Square Errors (RMSE) at increasing k-step horizons.

Second, the loadings estimated in (2.2) are unconditional and measure the elasticity of real GDP growth to base asset returns. For identification, we require variation in real GDP growth due to monetary news. In practice, it is likely that non-monetary news has systematic effects on asset returns. For example, stock returns can increase in response to high productivity growth, while an oil price shock could have negative effects on stock prices of firms that rely on oil inputs. For the unconditional loadings to be an accurate predictor of how real GDP growth reacts to monetary news, we require the base assets to respond similarly to both monetary and non-monetary news shocks. For a formal proof of the conditions required for the loadings estimated in (2.3) to be unbiased, we refer the reader to **Appendix B**.

2.4 Data

High-Frequency Identification of Monetary Policy Shocks

Consistent with the work of Kuttner (2001), Gurkaynak et al. (2004), and Bernanke and Kuttner (2005), among others, we define a U.S. monetary policy shock as the component of monetary policy unanticipated by market participants. Specifically, this shock is constructed using interest rate futures for the U.S. Federal Funds rate traded on the Chicago Mercantile Exchange (CME). These financial instruments are contracts with payouts at maturity based on the average effective Federal Funds rate during the month of expiration. Prices of these liquid contracts are directly tied to expectations of target U.S. Federal Funds rates, rendering them crucial for policy analysis. They provide a good signal of what investors anticipate the future path of interest rates may be with high likelihood, as well as a prediction of the outcome for future FOMC meetings. Changes in the futures rate during a short time window around an FOMC announcement provide a measure of the unanticipated component of the change in the Federal Funds rate.

This market-based approach rests on the identifying assumption that the Federal Funds futures contract is a valid instrumental variable for monetary policy. Specifically, the futures price must be sufficiently correlated with the "true" monetary policy stance. Moreover, during an FOMC announcement, the contract price must only respond to news about monetary policy. This market-based measure must not be correlated with any other news, such as news related to the state of economy during the announcement window.

Following Gurkaynak et al. (2004), we construct the intraday change in the futures rate 15 minutes prior to and 45 minutes after the FOMC announcement (see **Figure 2.1**):

$$\Delta f1_{US,t} = f1_{US,t+45} - f1_{US,t-15} \tag{2.5}$$

In analyzing the current-month contract, it is worth noting the contract settlement price is based on what investors think the monthly Federal Funds rate is for the current month. For an event taking place on day d_0, the day of the closest FOMC announcement, with D_0 days in that month, the surprise target Federal Funds rate change is calculated from the change in the rate implied by the current-month futures contract. The change in the implied 30-day futures rate $\triangle f1_{US,t}$ must be scaled up by a factor related to the number of days in the month affected by the change, which is equal to $D_0 - d_0$ days.[7]

$$MP1_{US,t} = \frac{D_0}{D_0 - d_0} \Delta f1_{US,t} \tag{2.6}$$

While using near-month interest rate futures contracts for the underlying policy rate enable us to construct monetary surprises in short-term interest rates, these contracts are limited in use during episodes of unconventional monetary policy. Changes in near-month futures contracts do not exhibit sufficient variation resulting from constraints imposed by the ZLB. Furthermore, Federal Reserve policies such as quantitative easing, which have typically involved central bank asset purchases of long-term bonds, as well as forward guidance, which anchor long-term interest rates to be low for a considerable period of time, are insufficiently captured by the short-end of the futures contract's term structure.

A more useful way to measure unanticipated monetary policy shocks *across* the maturity space is to augment the CME contracts with U.S. Treasury yields. Along with the futures rate contracts, we use changes in 3-month and 2-year U.S. Treasury bond yields around FOMC announcements. These changes are also taken 15 minutes before and 45 minutes after the FOMC's decision is made public. Consistent with the methodology in Gurkaynak (2005), we decompose U.S. monetary policy shocks into three surprise components: *timing*, *level*, and *slope*.

The *level* surprise measures a parallel shift in interest rate expectations over a horizon of 3 to 6 months. This measure uses the change in the 3-month U.S. Treasury yield around FOMC announcements:

$$\Delta US3MT_{i,t} = level_t \tag{2.7}$$

Timing is then estimated as the residual of the near-month 30-day futures contract $MP1_{US,t}$ in an ordinary least squares estimation procedure which regresses $MP1_t$, defined in (2.6), on the *level* component (2.7). *Timing* captures shocks to the stance in U.S. monetary policy not already incorporated in the 3-month U.S. Treasury yield. It therefore captures transitory news unaccounted for within a 3-month policy horizon, i.e.

$$MP1_{US,t} = \alpha_1 + \beta_1 level_t + \underbrace{timing_t}_{\text{residual}} \tag{2.8}$$

[7] We can also construct surprises in changes of expected rates at longer horizons. For example, surprises in the expected Federal Funds rate after the 2^{nd} and 3^{rd} FOMC announcements are given by $MP2_{US,t} = \left[\Delta f2_t - \frac{d_2}{D_2} MP1_{US,t}\right] \frac{D_2}{D_2 - d_2}$ and $MP3_{US,t} = \left[\Delta f3_t - \frac{d_3}{D_3} MP2_{US,t}\right] \frac{D_3}{D_3 - d_3}$, respectively.

Lastly, *slope* is constructed to be orthogonal to both *level* and *timing*. *Slope* captures revisions to interest rate changes at the long-end of the yield curve, with horizons ranging from 2 to 10 years. Therefore, *slope* captures a decline in the term premium as well as whether unconventional monetary policy exerts a significant flattening of the yield curve through a compression in yields. We estimate the *slope* component as the residual in a linear regression of changes in 2-year U.S. Treasury yields (around FOMC announcements) against *timing* and *slope*. This is shown in the specification below:

$$\Delta US2YT_{i,t} = \alpha_2 + \gamma_2 timing_t + \beta_2 level_t + \underbrace{slope_t}_{\text{residual}} \tag{2.9}$$

For the two other countries in our analysis, Australia and Canada, we implement a similar procedure, albeit with some changes. Because, there do not exist liquid futures contracts tied to the policy rates of the Reverse Bank of Australia (RBA) and the Bank of Canada (BOC), as is the case with the U.S. Federal Reserve, we compute surprises in futures contracts whose underlying is the yield in the RBA's and BOC's 90-day/3-month interbank rate.[8] The use of futures contracts tied to both the RBA's and BOC's 90-day/3-month interbank rate is not new and supported in past works (e.g. Ranaldo and Rossi, 2010; Brusa et al., 2016).

For both Australia (AUS) and Canada (CAN), equations for *timing*, *level*, and *slope* are similarly defined, with the sole difference being the use of 90-day interest rate futures contracts in the construction of *timing*. Generalizing to a given country $c \in \{US, AUS, CAN\}$, $\Delta c3MT_t$ and $\Delta c2YT_t$ denote changes in 3-month and 2-year government Treasuries 15 minutes prior to and 45 minutes after country c's central bank announces its policy:

$$MP_{c,t} = \alpha_1 + \beta_1 level_{c,t} + timing_{c,t} \tag{2.10}$$

$$\Delta c3MT_t = level_{c,t} \tag{2.11}$$

$$\Delta c2YT_t = \alpha_2 + \beta_2 level_{c,t} + \gamma_2 timing_{c,t} + slope_{c,t} \tag{2.12}$$

A brief description of interest rate futures for a given central bank's policy rate is provided in **Table 2.1**. Summary statistics for the *timing*, *level*, and *slope* surprises are displayed in **Table 2.2**.

Base Assets Used in Replicating Portfolios

The list of financial base assets used in the construction of our replicating portfolios for the U.S., Canada, and Australia are provided in **Tables 2.3**, **2.4**, and **2.5**. All data at the daily frequency are from Global Financial Data (GFD). For high-frequency data (i.e. tick-by-tick data), such as government (Treasury) yields, exchange rates, equities, and commodity indices, we use Thomson Reuters Tick History and CQG Portara.

[8] In fact, outside of the U.S., there do not exist liquid contracts analogous to the 30-day Federal Funds futures instrument.

We select the base asset set by starting with an unfiltered list of asset returns for each country. Some assets, such as major equity indices of small, mid, and large market capitalization firms, major exchange rates, commodities, and government Treasury yields, are selected automatically as part of the portfolio. The remaining variables are optimally selected based on maximizing the adjusted R^2 of the in-sample fit.[9]

We now provide evidence of asset price responses around monetary policy announcements. **Table 2.6**, documents the high-frequency response of a set of U.S. base assets to the *timing*, *level*, and *slope* surprises around FOMC announcements. A contractionary shock to *level* causes an appreciation of the US Dollar/Euro exchange rate.[10] The term spread ($TERM^{US,10Y-2Y}$), defined as the difference between 10-year and 2-year U.S. Treasury yields, responds negatively to *slope*. The two major U.S. stock indices, the S&P500 and Dow Jones Industrial Average (DJIA), respond negatively only to *timing*. Their response is similar in magnitude to the baseline estimates of FOMC surprise effects on stock prices documented in Bernanke and Kuttner (2005).

The effects of Australia's monetary surprises on a set of its base assets are presented in **Table 2.7**. **Table 2.8** provides analogous results for Canada. For Australia, a contractionary surprise in *slope* results in an appreciation of the AUD/USD exchange rate, a rise in the term spread, and a contraction in the ASX50 Mid Cap index. For Canada, a contractionary *slope* results in a decline in its stock and commodity return indices, as well as a decline in the term spread between 10- and 2-year government bonds.

We also find significant effects of FOMC announcements on the same set of base assets studied for Australia and Canada. Specifically, a one basis point rise in *timing* results in a ten basis point decline in Canada's stock prices, a two-and-a-half basis point depreciation of the Canadian dollar, and a significant decline in the term spread as short-term rates rise by more than long-term rates. All three responses are statistically significant at the 5% significance level. We also observe similar responses in Australia's asset returns. Altogether, these findings are consistent with recent empirical studies documenting a significant effect of U.S. monetary surprises on bond yields and stock indices in a wide set of countries (Curcuru et al., 2018; Kearns et al., 2018).

2.5 Empirical Evidence

In this section, we first present robustness tests of the replicating portfolio methodology described in **Section 2.5**. We demonstrate the adjusted R^2 of the GDP-tracking portfolios are sufficiently high. In addition, the portfolios perform reasonably well out-of-sample. We then test for the effects of domestic monetary policy surprises on real GDP-tracking news for the U.S., Australia, and Canada. We find changes in *slope* have significant effects on

[9]Additionally, we allow the set of base assets to change for replicating portfolios at different horizons. However, for brevity we only report the relevant replicating portfolio for the 1-quarter horizon.

[10]Exchange rates are expressed as Dollars/per Euro. For brevity the Dollar/Euro exchange rate is shown, however similar results hold for other currencies vis-á-vis the dollar.

real GDP-tracking news, and are consistent with other empirical studies on the effects of monetary policy. Lastly, we examine the spillovers of FOMC announcements to Australia and Canada through the response of these two countries' real GDP-tracking news measures to U.S. *timing*, *level*, and *slope*.

Real GDP-Tracking News: Performance of Replicating Portfolios

The first step of our real GDP-tracking approach is presented in **Table 2.11**. We estimate (2.2), which is the real GDP replicating portfolio at a quarterly frequency for horizon $k = 1$ through horizon $k = 12$. We demonstrate the robustness of our replicating portfolios by computing the adjusted R^2 of the real GDP-tracking portfolio measures. This provides one way of assessing whether we capture sufficient unconditional variation in real GDP growth through our financial base assets.

For all three countries, the replicating portfolios tend to perform reasonably well at longer horizons, with adjusted R^2 increasing from 0.61 to 0.99 for the U.S. as we move from $k = 1$ to $k = 12$ quarters. Similar result are obtained for both Australia and Canada: adjusted R^2 rises from a minimum of 0.4 (0.5) at $k = 1$ to 0.94 (0.98) at $k = 12$.

We then conduct out-of-sampling fit tests by comparing the fit of our tracking/replicating portfolios to a random walk at horizons $k = 1$ through $k = 12$. The equation for Root Mean Square Error (RMSE) at horizon k is given in (2.13), where k is the forecast horizon, N_k is the total number of forecasts in the projection period, $\widehat{\Delta y_{t+s+k}}$ is the fitted values of the real GDP-tracking portfolio, and Δy_{t+s+k} is realized real GDP growth. The construction of the RMSE ratios involves taking the ratio of $rmse_{realGDP}$ to the RMSE obtained from a random walk, in which the current quarter's real GDP growth forecast is taken to be the previous quarter, with similar forecasts made at different horizons.

The results are provided in **Table 2.11**. For the U.S., the RMSE ratio is 0.72 at $k = 1$ and slightly increases to 0.79 at $k = 12$, while for Australia and Canada the RMSE ratio is 1.2 and 0.23 at $k = 12$, respectively. Underlying this trend is the fact that at longer horizons, the rolling regression sample is vastly reduced in comparison to a shorter horizon.

$$rmse_{rGDP} = \left(\frac{\sum_{s=0}^{N_k-1} \left[\widehat{\Delta y_{t+s+k}} - \Delta y_{t+s+k} \right]^2}{N_k} \right)^{\frac{1}{2}} \tag{2.13}$$

Response of Real GDP-Tracking News to Domestic Monetary Announcements

Having established robustness of the replication portfolio methodology, we estimate (2.4) by regressing the high-frequency, real GDP-tracking news measure (for each country) on domestic *timing*, *level*, and *slope* coefficients to infer the causal effect of monetary policy shocks on real GDP growth. Our results for a contractionary one-percent surprise in each of the three surprise components for the U.S., Australia, and Canada are provided in **Tables 2.6**, **2.7**, and **2.8**, respectively. The change in long-term spreads captured by *slope* has a negative impact on news at most horizons, with peak sensitivity for the replicating portfolio at a horizon of 6 quarters for the U.S., and 10 quarters for both Australia and Canada. The U.S. result is consistent with findings in previous studies (Romer and Romer, 1989; Romer and Romer, 2004; Gertler and Karadi, 2015). These earlier studies find a peak response of output following a monetary policy shock occurs after 6 to 9 quarters.

Given these estimates, a shock in the Federal Reserve *slope* component of one percent results in approximately a 1.9 percent decline in real GDP growth. Since the *slope* component has a sample standard deviation of 7 basis points, this suggests a rather quantitatively small effect of monetary announcements on real GDP growth. However, our estimates are within range of results documented in other papers. For example, Gertler and Karadi (2015) estimate impulse responses of industrial production growth with respect to a 25 basis point shock in the 1-year bond rate and find a significant effect on industrial production of approximately 0.3 to 0.5 percent 15 to 20 months after the impact.

For both the RBA and BOC monetary announcements, the domestic *slope* coefficient is similar in magnitude. The effect of *slope* on output growth peaks after 6 quarters, with a one percent contraction in *slope* resulting in a 1.3 to 1.5 percent cumulative decline in real GDP-news growth over that horizon (see **Tables 2.6** and **2.8**).

Interestingly enough, the results are predominantly driven by each country's *slope* component, as opposed to the *level* or *timing* components of monetary policy. Intuitively, *slope* predominantly matters since changes in longer-term Treasury yields are more important for determining the long-run causal impact of monetary policy. As an economy enters a recession, long-term yields fall as central banks pursue expansionary policies to bolster the economy out of a recession. In contrast, tightening of monetary policy in a boom period, due to concerns of high inflation, lead to higher long-term yields in order to dampen high economic growth. To show robustness, we plot the slope coefficients of domestic monetary announcements at different horizons for the U.S., Australia, and Canada in **Figures 2.2**, **2.3**, and **2.4**.

Response of Australia and Canada's Real GDP-Tracking News to Federal Reserve Announcements

We now test for the international spillover effects of U.S. monetary policy. As before, we estimate (2.4), but with a notable difference: we construct real GDP-tracking news for both Australia and Canada based on domestic asset returns around FOMC announcements.

Results for Australia are summarized in **Table 2.15**. Our findings suggest that at most horizons, the *level* component of U.S. monetary policy has a significantly strong negative impact on Australia's real GDP-tracking news. Quantitatively, we find that a one basis point rise in medium-term interest rates results in a 0.3 percent decline in Australia's real GDP-tracking news after four quarters. These spillover effects are quantitatively smaller than domestic effects, which is intuitive given that opposing channels (such as expenditure switching) are likely to attenuate the response.

These results, taken at face value, yield supportive evidence of the theory set forth in Rey et al. (2013). This theory posits that a hike in U.S. interest rates can lead to a contraction in global bank credit, leverage and asset prices. In this case, even with a flexible exchange rate regime, Australia can only obtain sovereign monetary policy if it imposes capital controls. Otherwise, the economy's credit flows are driven by U.S. monetary policy, which in turn has real macroeconomic effects. This evidence is consistent with other recent papers on spillover effects, such as Dedola et al. (2017). In that paper, the authors use an SVAR to estimate the effects of U.S. monetary policy shocks on a set of advanced and emerging markets. For both economy types, they document that a one standard deviation surprise tightening in U.S. monetary policy results in a peak decline of approximately 0.2 percent in real GDP growth after four quarters.

Results for Canada are provided in **Table 2.16**; they are mixed. While the effects at a short horizon suggest a contraction in the U.S. results in an expansion of Canada's real GDP growth, with a one basis point decline in short-term interest rates resulting in a one basis point rise in real GDP-tracking news, the results at longer horizons are unclear. To explain the short-term expansionary effect for Canada, conventional theory is based on expenditure switching effects of an exchange rate depreciation. As the Canadian dollar depreciates, this lowers the price of exports and raises the price of imports, leading to expenditure switching effects as foreigners demand more exports. The expenditure switching effects are likely to dominate as Canada is heavily reliant on trade with the United States. An aggregate measure of trade exposure suggests that up to 50% of trade in exports and imports for Canada is with the U.S. (Dedola et al., 2017).

To summarize our results, we plot the coefficients of the FOMC *level* component on Australia's real GDP-tracking news in **Figure 2.5**, and the FOMC *slope* component on Canada's real GDP news in **Figure 2.6**.

2.6 Conclusion

We provide a novel method for estimating real GDP-tracking news based on a set of base asset returns. Our real GDP-tracking method offers a novel way for thinking about the causation of monetary policy to real GDP growth. By replicating real GDP growth via a portfolio of assets at a low frequency, we construct a proxy for high-frequency real GDP-tracking news based on the replicating portfolio's responses around monetary announcements.

Our procedure enables us to not only examine domestic effects, but also spillover effects from a center country's monetary announcements to a country in its sphere of influence. We illustrate this by considering the effects U.S. Federal Reserve monetary policy exerts on both Australia and Canada's real GDP-tracking news measures. First, we find that contractionary shocks in the U.S., Australia, and Canada result in declining real GDP growth. Specifically, in response to a one basis point rise in long-term yields, output growth falls between 1.5 to

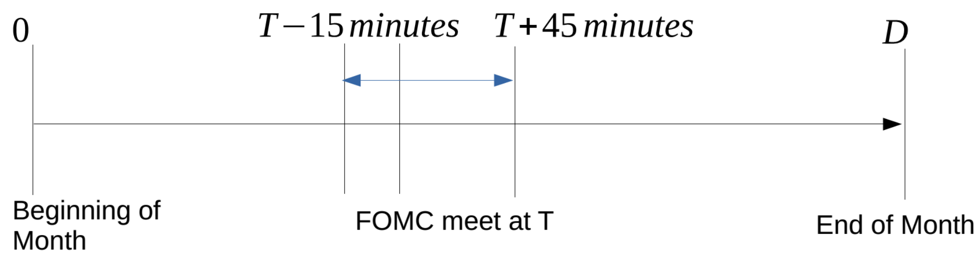
2.0 basis points after six quarters. These estimates are in line with other empirical studies using SVAR methods to quantify the effects of monetary policy on real GDP growth (e.g. Gertler and Karadi, 2015).

Secondly, we test for whether FOMC announcements result in significant changes to the real GDP-tracking news measures of both Australia and Canada. For Australia, we find that a rise in U.S. interest rates results in a contraction of Australia's real GDP-tracking news at most horizons. This lends support to the theory of the global financial cycle put forth in Rey et al. (2013), in which a contraction in U.S. monetary policy results in declining bank asset prices, global leverage, and consequently, declining credit to periphery countries.

Contrarily, for Canada, a rise in U.S. short-term interest rates results in expansionary effects in the short-run. This suggests expenditure switching effects may be the dominating channel following U.S. monetary policy. Specifically, contractionary policy by the U.S. Federal Reserve, which results in the depreciation of the Canadian dollar, then leads to an expansion in net exports.

Going forward, the methodological contribution in this chapter can also be used to study the effects of U.S. monetary policy on emerging markets. While it is intuitive that U.S. monetary policy has a significant effect on Australia and Canada, a similar regime of influence may exist in Europe with the European Central Bank (ECB) potentially exerting similar effects on periphery countries outside the Eurozone. Understanding these effects are feasible with our approach. This analysis would provide crucial insights into the effectiveness of monetary policy, which would aid in setting optimal policy.

Figure 2.1: Computing U.S. Federal Funds Rate Shocks



Note: Following Gurkaynak et al. (2004), we construct a "wide" window around each FOMC announcement at time T to compute the futures rate change. Intraday changes are based on the change in the futures rate 15 minutes *prior* to and 45 minutes *after* the announcement.

Figure 2.2: Response of U.S. Real GDP-Tracking News to FOMC *slope*

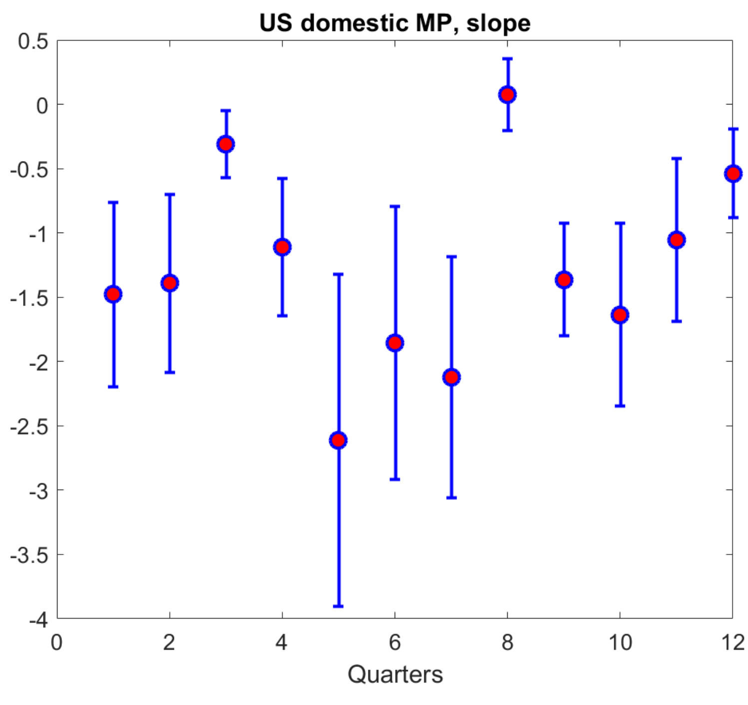


Figure 2.3: Response of Australia's Real GDP-Tracking News to RBA *slope*

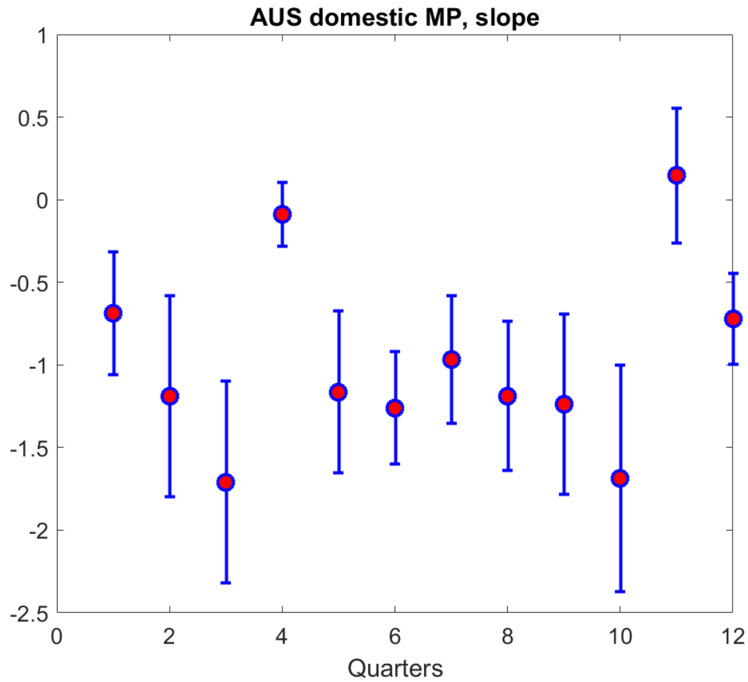


Figure 2.4: Response of Canada's Real GDP-Tracking News to BOC *slope*

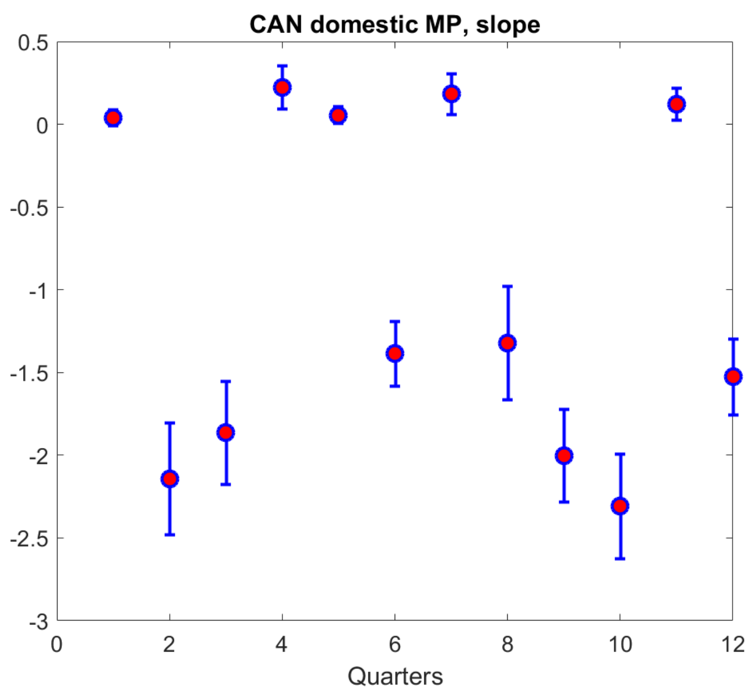


Figure 2.5: Response of Australia's Real GDP-Tracking News to FOMC *level*

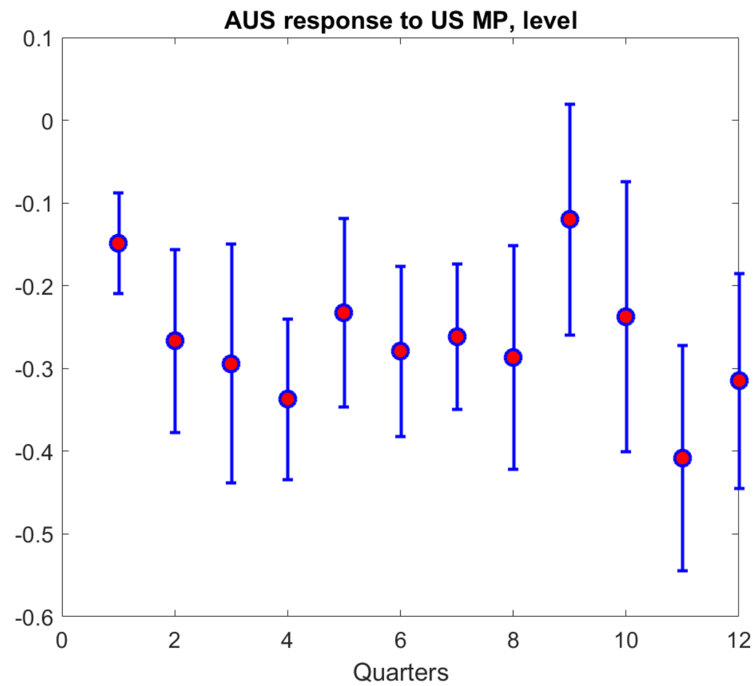


Figure 2.6: Response of Canada's Real GDP-Tracking News to FOMC *slope*

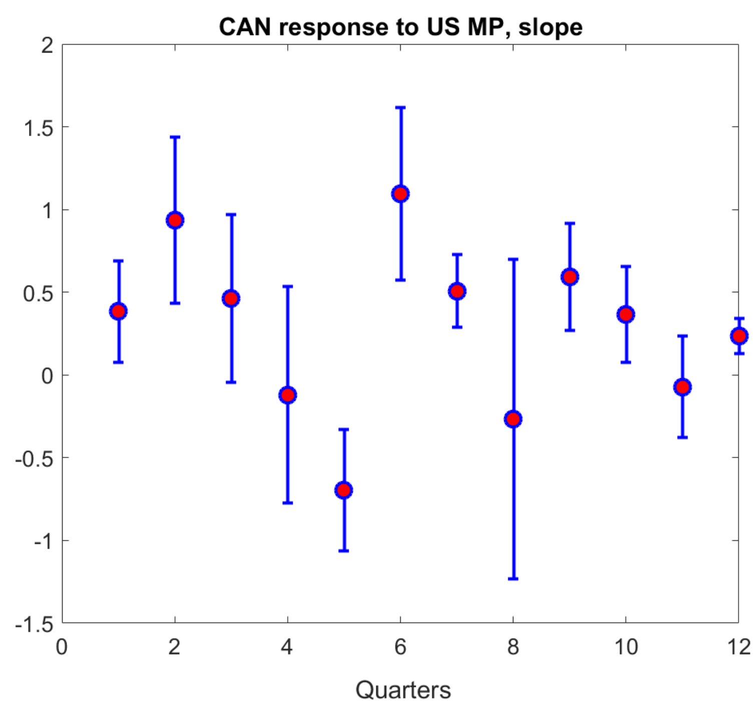


Table 2.1: Interest Rate Futures Contracts for the U.S., Australia, and Canada

Country	Underlying Policy Rate	Monetary Policy Shock
US	Federal Funds Rate	$MP1_{US,t} = \frac{D}{D-d}\Delta f1_{US,t}$
AUS	SFE 90-day Bank Accepted Bill Rate	$MP_{AUS,t} = \Delta f1_{AUS,t}$
CAN	ME 90-day Bankers' Acceptance Rate	$MP_{CAN,t} = \Delta f1_{CAN,t}$

Table 2.2: Monetary Policy Surprises for the U.S., Australia, and Canada - Summary Statistics

	Mean	**SD**	**p5**	**p25**	**Median**	**p75**	**p95**	**Announcements**
$timing_{\text{US}}$	9.6e-11	.044	-.077	-.006	.00067	.0088	.081	184
$level_{\text{US}}$	-.021	.14	-.16	-.016	-.0025	.005	.11	185
$slope_{\text{US}}$	5.3e-11	.07	-.12	-.029	.004	.033	.11	184

U.S. Federal Reserve scheduled announcements from 2/1994 to 12/2016.

	Mean	**SD**	**p5**	**p25**	**Median**	**p75**	**p95**	**Announcements**
$timing_{\text{AUS}}$	-.00013	.019	-.027	-.0065	.0011	.0086	.021	255
$level_{\text{AUS}}$	.0026	.052	-.06	-.01	0	.02	.05	255
$slope_{\text{AUS}}$	.00028	.069	-.12	-.025	.0027	.035	.11	222

RBA scheduled announcements from 3/1990 to 12/2016.

	Mean	**SD**	**p5**	**p25**	**Median**	**p75**	**p95**	**Announcements**
$timing_{\text{CAN}}$	2.2e-12	.0089	-.012	-.0052	-.00021	.0048	.012	130
$level_{\text{CAN}}$	.0005	.02	-.03	-.01	0	.01	.03	130
$slope_{\text{CAN}}$	2.8e-10	.18	-.12	-.048	-.016	.019	.11	130

BOC scheduled announcements from 12/2000 to 12/2016.

Table 2.3: Base Assets for the U.S.

Currency	Stock Indices	Commodities	Bond Yields/Other
EUR/USD	S&P500	ICE Brent Crude Oil	Treasuries: 3m, 6m, 2Y, 5Y, 10Y, 30Y
GBP/USD	S&P Banks	NY MEX Nat Gas	Treasury spreads: 10Y-2Y, 30Y-2Y
CNY/USD	S&P Retail	COMEX Gold	Corp: 1-10Y
MXN/USD	S&P Healthcare	COMEX Silver	Corp: 10+Y
	S&P Industrials	S&P GSCI Agr	S&P500 VIX
	S&P Financials	S&P GSCI Livestock	ML 1m-Vol (MOV)
	DJ Transports	S&P GSCI TR	
	DJ Banks	S&P GSCI Pmetals	
	DJ Utilities	S&P GSCI Imetals	
	DJ Oil & Gas		
	DJ Real Estate Index		
	Russell 2000		
	Nasdaq Composite 100		

Table 2.4: Base Assets for Australia

Currency	Stock Indices	Commodities	Bond Yields/Other
AUD/USD	ASX200 All Ord	ICE Brent Crude Oil	Treasuries: 3m, 2y, 5y, 10y, 15y
AUD/JPY	ASX50 Large Cap	NY MEX Nat Gas	Treasury spreads: 10Y-2Y, 15Y-2Y
AUD/EUR	ASX50 Mid Cap	COMEX Gold	Corp: 1-10Y
AUD/GBP	ASX200 Small Ord	COMEX Silver	Corp: All maturities
	ASX200 Banking	S&P GSCI Agr	S&P500 VIX
	ASX200 Energy	S&P GSCI Livestock	ML 1m-Vol (MOV)
	ASX200 Utilities	S&P GSCI TR	
	ASX200 Materails	S&P GSCI Pmetals	
	ASX200 Small Ord	S&P GSCI Imetals	

Table 2.5: Base Assets for Canada

Currency	Stock Indices	Commodities	Bond Yields/Other
CAD/USD	CDNX Comp, TSX300 Comp	ICE Brent Crude Oil	Treasuries: 3m, 6m, 2Y, 5Y, 10Y, 30Y
CAD/EUR	TSX300 Comp	NY MEX Nat Gas	Treasury spreads: 10Y-2Y, 30Y-2Y
CAD/CNY	TSX60 Large Cap	COMEX Gold	Corp: 1-10Y, 5-10Y, 15Y
CAD/JPY	TSX Banks	COMEX Silver	Corp: 10+Y
CAD/MSXN	TSX Gold	S&P GSCI Agr	S&P500 VIX
	TSX60 Large Cap	S&P GSCI Livestock	ML 1m-Vol (MOV)
	TSX Energy	S&P GSCI TR	
	TSX IT	S&P GSCI Pmetals	
	TSX Materials	S&P GSCI Imetals	
	TSX Consumer Disc		

Table 2.6: Response of U.S. Asset Returns to FOMC Announcements

	S&P500	EUR/USD	$TERM^{\text{US,10-2Yr}}$	S&P500 Vol	S&P GSCI TR
$timing_{\text{US}}$	-5.7***	-2.7***	-.35**	6.5***	-3
	(-3.5)	(-2.8)	(-2.2)	(2.9)	(-1.2)
$level_{\text{US}}$	1	-.35*	-.059**	-1.2	.33
	(1.1)	(-1.8)	(-2.2)	(-1.2)	(.69)
$slope_{\text{US}}$	-1.2	-2.3***	-.36***	.48	-2.8*
	(-1.1)	(-3.8)	(-3.1)	(.39)	(-1.8)
adjusted R^2	.14	.14	.19	.1	.027
Events	168	183	184	168	184

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

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

Table 2.7: Response of Australia's Asset Returns to RBA Announcements

	ASX50 MCap	AUD/USD	$SPREAD^{\text{AUS,allYr}}$	S&P GSCI TR
$timing_{\text{AUS}}$	-1.1	-.97	.68	.88
	(-.32)	(-.2)	(1.6)	(.1)
$level_{\text{AUS}}$	-1.3	-.18	-.12	.21
	(-.88)	(-.09)	(-1.1)	(.038)
$slope_{\text{AUS}}$	-2***	3.1***	.25**	-.56
	(-3.1)	(3.1)	(2.5)	(-.31)
adjusted R^2	.097	.074	.21	.00079
Events	222	222	211	222

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

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

Table 2.8: Response of Canada's Asset Returns to BOC Announcements

	MSCI-Can ETF	CAD/USD	$TERM^{\text{CAN,10-2Yr}}$	S&P GSCI TR
$timing_{\text{CAN}}$	16	4.8	-1.8**	-13
	(.89)	(.96)	(-2.2)	(-1)
$level_{\text{CAN}}$	9.1	2.6	-.91*	12**
	(1.4)	(1.3)	(-1.8)	(2.2)
$slope_{\text{CAN}}$	-.59*	.47	-1.9***	-.75***
	(-1.8)	(.8)	(-10)	(-2.7)
adjusted R^2	.041	.051	.93	.041
Events	130	129	130	130

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

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

Table 2.9: Response of Australia's Asset Returns to FOMC Announcements

	ASX50 MCap	AUD/USD	$SPREAD^{\text{AUS,allYr}}$	S&P GSCI TR
$timing_{\text{US}}$	-.048	-2.8***	-.013	-3
	(-.11)	(-2.8)	(-.13)	(-1.2)
$level_{\text{US}}$	-.0088	-.3*	-.071*	.33
	(-.095)	(-1.7)	(-2)	(.69)
$slope_{\text{US}}$	-.18	-3.1***	.0027	-2.8*
	(-1.3)	(-3.9)	(.063)	(-1.8)
adjusted R^2	.0085	.13	.039	.027
Events	168	183	160	184

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

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

Table 2.10: Response of Canada's Asset Returns to FOMC Announcements

	MSCI-Can ETF	CAD/USD	$TERM^{\text{CAN,10-2Yr}}$	S&P GSCI TR
$timing_{\text{US}}$	-9.5***	-2.5***	-.32***	-3
	(-4.4)	(-3.7)	(-3.3)	(-1.2)
$level_{\text{US}}$	.38	-.066	-.043	.33
	(.44)	(-.57)	(-1.2)	(.69)
$slope_{\text{US}}$	-1.8	-1.9***	-.099*	-2.8*
	(-1.3)	(-3.3)	(-1.7)	(-1.8)
adjusted R^2	.15	.12	.016	.027
Events	167	183	168	184

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

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

Table 2.11: 1^{st}-Step Results - RMSE and adjusted R^2 for Replicating Portfolios

Country		$k=1$	$k=2$	$k=4$	$k=6$	$k=8$	$k=10$	$k=12$
US	$\overline{R^2}$	.61	.77	.91	.96	.98	.98	.99
	RMSE	.72	.95	.66	.54	.86	.75	.79
	N	88	87	85	83	81	79	77
Australia	$\overline{R^2}$	.4	.54	.8	.9	.89	.93	.94
	RMSE	.6	.92	.87	.84	1.8	1.5	1.2
	N	82	81	79	77	75	73	71
Canada	$\overline{R^2}$	.5	.8	.94	.94	.98	.97	.98
	RMSE	.71	.79	.55	.5	.73	.7	.23
	N	77	76	74	72	70	68	66

Table 2.12: Response of U.S. Real GDP-Tracking News to Domestic *timing*, *level*, and *slope*

	$k=1$	$k=2$	$k=4$	$k=6$	$k=8$	$k=10$	$k=12$
$timing_{\text{US}}$	-1.2	-.85	-.67	-1.6	.3	-1.5	.057
	(-1.2)	(-.87)	(-.83)	(-1.1)	(.62)	(-1.3)	(.1)
$level_{\text{US}}$	-.13	-.21*	-.2**	-.39**	.022	-.092	.079
	(-1.1)	(-1.8)	(-2.2)	(-2.3)	(.26)	(-.71)	(.84)
$slope_{\text{US}}$	-1.5**	-1.4**	-1.1**	-1.9*	.075	-1.6**	-.54
	(-2.1)	(-2)	(-2.1)	(-1.7)	(.27)	(-2.3)	(-1.6)
R^2	.032	.029	.03	.021	.0034	.042	.017
Events	184	184	184	184	184	184	184

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 2.13: Response of Australia's Real GDP-Tracking News to Domestic *timing*, *level*, and *slope*

	$k=1$	$k=2$	$k=4$	$k=6$	$k=8$	$k=10$	$k=12$
$timing_{\text{AUS}}$	-1.7	-3.6*	-.31	-1.4	-1.1	-2	-.25
	(-1.2)	(-1.8)	(-.33)	(-1.2)	(-.72)	(-1)	(-.19)
$level_{\text{AUS}}$	-.41	-.55	.028	-1.1	-1.1	-1.5	-1.1
	(-.56)	(-.44)	(.057)	(-1.2)	(-.92)	(-.86)	(-1.4)
$slope_{\text{AUS}}$	-.69*	-1.2*	-.088	-1.3***	-1.2***	-1.7**	-.72***
	(-1.8)	(-2)	(-.45)	(-3.7)	(-2.6)	(-2.5)	(-2.6)
R^2	.027	.027	.0012	.051	.025	.021	.046
Events	222	222	222	222	222	222	222

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 2.14: Response of Canada's Real GDP-Tracking News to Domestic *timing*, *level*, and *slope*

	$k=1$	$k=2$	$k=4$	$k=6$	$k=8$	$k=10$	$k=12$
$timing_{\text{CAN}}$	-.09	-2.6	2.1	-2.2	-.097	-4.3**	-1.5
	(-.11)	(-1.5)	(.91)	(-1.2)	(-.038)	(-2.1)	(-.97)
$level_{\text{CAN}}$	-.31	-.72	-2.2	-1.5	-3.6	-1.5	.56
	(-.71)	(-.6)	(-1.2)	(-1.2)	(-1.5)	(-1.3)	(.71)
$slope_{\text{CAN}}$	.037	-2.1***	.22*	-1.4***	-1.3***	-2.3***	-1.5***
	(.78)	(-6.3)	(1.7)	(-7.2)	(-3.9)	(-7.3)	(-6.6)
R^2	.016	.73	.021	.48	.23	.73	.79
Events	130	130	130	130	130	130	130

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 2.15: Response of Australia's Real GDP-Tracking News to U.S. *timing*, *level*, and *slope*

	$k=1$	$k=2$	$k=4$	$k=6$	$k=8$	$k=10$	$k=12$
$timing_{\text{US}}$	.46	1.1	-.28	.08	1.3	1.6	-.65
	(.56)	(.67)	(-.62)	(.071)	(.9)	(.71)	(-.99)
$level_{\text{US}}$	-.15**	-.27**	-.34***	-.28***	-.29**	-.24	-.31**
	(-2.4)	(-2.4)	(-3.5)	(-2.7)	(-2.1)	(-1.5)	(-2.4)
$slope_{\text{US}}$	.27	.47	-.74**	-.15	.5	1.1	-.81*
	(.71)	(.66)	(-2.4)	(-.28)	(.77)	(1.1)	(-2)
R^2	.0085	.0093	.056	.0056	.013	.012	.038
Events	184	184	184	184	184	184	184

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

Table 2.16: Response of Canada's Real GDP-Tracking News to U.S. *timing*, *level*, and *slope*

	$k = 1$	$k = 2$	$k = 4$	$k = 6$	$k = 8$	$k = 10$	$k = 12$
$timing_{\mathrm{US}}$	.87**	1.2*	.69	1.1	.78	.29	.3
	(2.2)	(1.9)	(.79)	(1.4)	(.63)	(.61)	(1.6)
$level_{\mathrm{US}}$	-.017	-.018	-.21*	.15	-.32**	.095	.026
	(-.28)	(-.17)	(-1.9)	(1.3)	(-2)	(1.4)	(.55)
$slope_{\mathrm{US}}$	.38	.93*	-.12	1.1**	-.27	.37	.24**
	(1.2)	(1.9)	(-.18)	(2.1)	(-.27)	(1.3)	(2.2)
R^2	.056	.033	.0068	.03	.008	.0068	.022
Events	184	184	184	184	184	184	184

t-statistics in parentheses. Heteroscedasticity-consistent and robust standard errors.

* $p < 0.1$, ** $p < .05$, *** $p < 0.01$

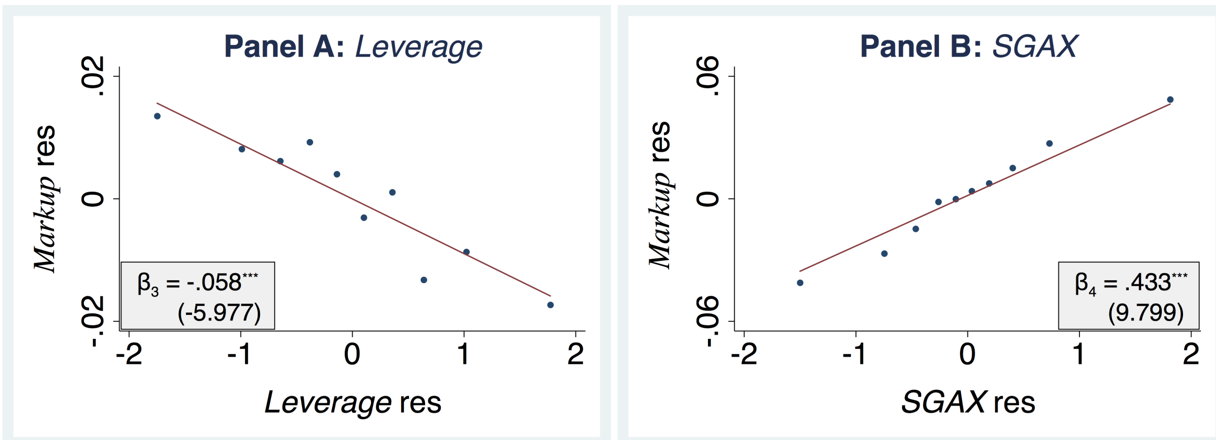
Appendix A

Appendix to Chapter 1

A.1 Additional Figures

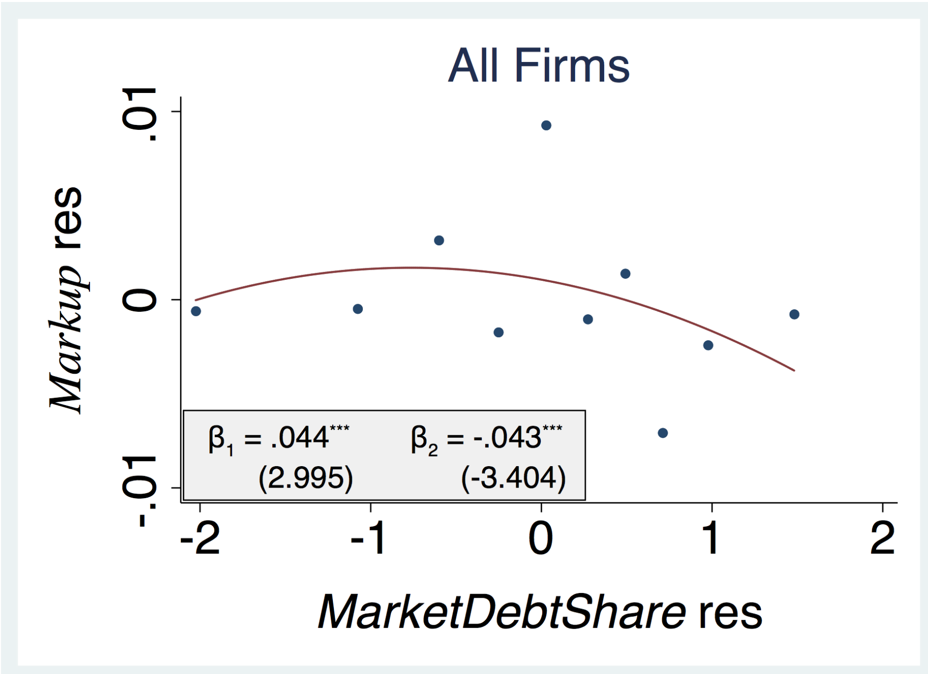
Estimation of Markups $\mathcal{M}$ with COGS as Variable Costs

Figure A.1: (Robustness) Relationship between $\mathcal{M}$ and *Leverage*, *SGAX*



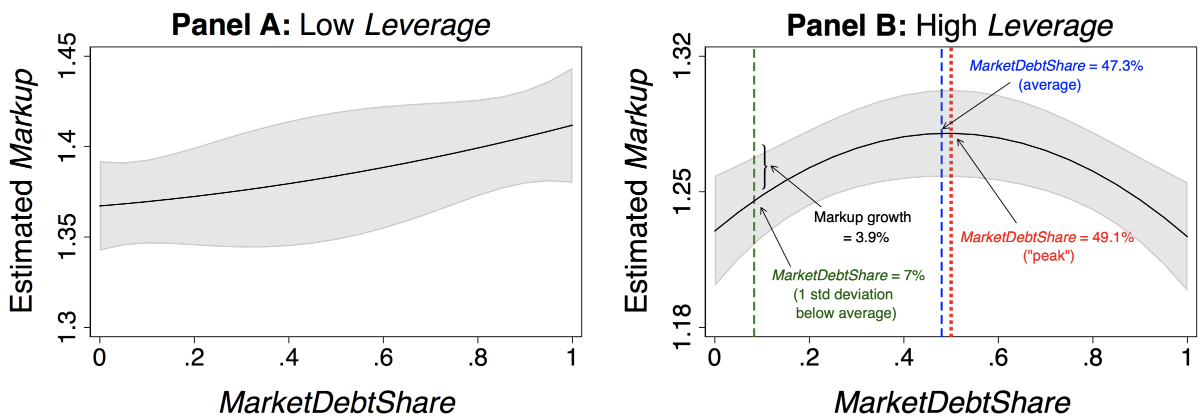
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with linear parametric estimates. In **Panel (A)**, the variable markup $\mathcal{M}$ and *Leverage* are residualized from $MarketDebtShare$, $MarketDebtShare^2$, $SGAX$, (5-digit) NAICS industry fixed effects, year fixed effects, and the following additional firm-level controls: lagged markup $\mathcal{M}$, size, age, sales growth, market-to-book ratio, cash, tangibility, profitability, interest rate coverage ratio, a dividend payout dummy, the Whited and Wu (2006) index, the Bodnaruk et al. (2015) index, as well as S&P credit rating binned fixed effects. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. *Leverage* is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. In **Panel (B)**, the variable markup $\mathcal{M}$ and $SGAX$ are residualized from $MarketDebtShare$, $MarketDebtShare^2$, *Leverage*, (5-digit) NAICS industry fixed effects, year fixed effects, and the following additional firm-level controls: lagged markup $\mathcal{M}$, size, age, sales growth, market-to-book ratio, cash, tangibility, profitability, interest rate coverage ratio, a dividend payout dummy, the Whited and Wu (2006) index, the Bodnaruk et al. (2015) index, as well as S&P credit rating binned fixed effects. *Leverage* and $SGAX$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best linear fit constructed using an OLS regression of $\mathcal{M}$ residuals on each respective set of "explanatory" residuals (*Leverage* or $SGAX$). In **Panel (A)**, the legend box (in gray) shows the point estimate for *Leverage* (β_3), while the legend box in **Panel (B)** shows the the point estimate for $SGAX$ (β_4), with t-statistics in parentheses. Standard errors are clustered by firm and year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.2: (Robustness) Relationship between $\mathcal{M}$ and $MarketDebtShare$



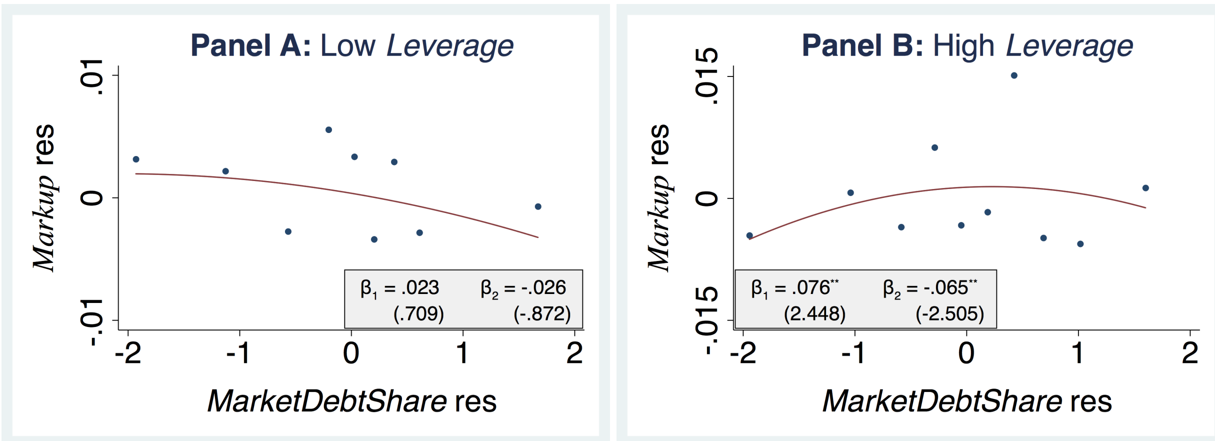
Note: This figure presents a non-parametric estimate of the CEF using a binned scatterplot, along with a quadratic parametric estimate. The variable markup $\mathcal{M}$ and $MarketDebtShare$ are residualized from $Leverage$, $SGAX$, (5-digit) NAICS industry fixed effects, year fixed effects, and the following additional firm-level controls: lagged markup $\mathcal{M}$, size, age, sales growth, market-to-book ratio, cash, tangibility, profitability, interest rate coverage ratio, a dividend payout dummy, the Whited and Wu (2006) index, the Bodnaruk et al. (2015) index, as well as S&P credit rating binned fixed effects. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. $MarketDebtShare$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals. The legend box (in gray) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.3: Estimated Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $Leverage$



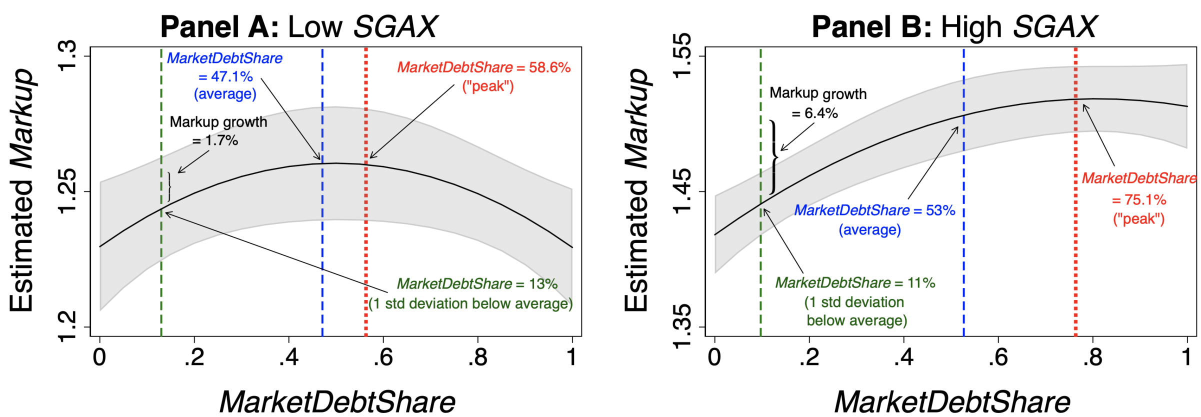
Note: This figure presents the estimated quadratic, hump-shaped relationship between $\mathcal{M}$ and $MarketDebtShare$ for firms in the lowest (**Panel (A)**) and the highest (**Panel (B)**) quartiles of $Leverage$ by year. For each group, $SGAX$ is evaluated at its mean value. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. The **gray** area represents 95% confidence intervals. In both panels, standard errors are clustered by firm and year.

Figure A.4: (Robustness) Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $Leverage$



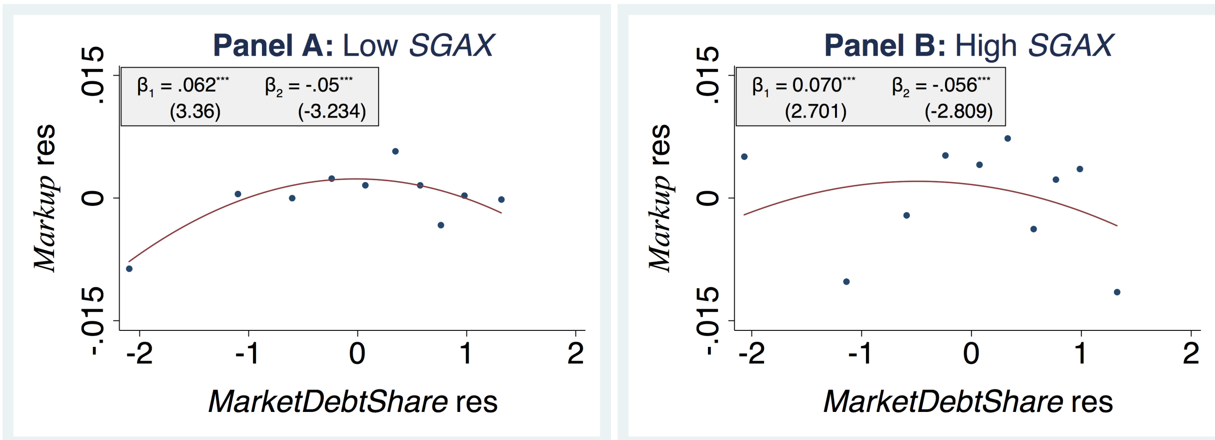
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. $Leverage$ is sorted into quartiles by year. The variable markup $\mathcal{M}$ and $MarketDebtShare$ are residualized from $SGAX$ for firms in the lowest (**Panel (A)**) and the highest quartile (**Panel (B)**), as well as (5-digit) NAICS industry fixed effects, year fixed effects, and the following additional firm-level controls: lagged markup $\mathcal{M}$, size, age, sales growth, market-to-book ratio, cash, tangibility, profitability, interest rate coverage ratio, a dividend payout dummy, the Whited and Wu (2006) index, the Bodnaruk et al. (2015) index, as well as S&P credit rating binned fixed effects.The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. For each group, $MarketDebtShare$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals for each group. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.5: Estimated Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SGAX$



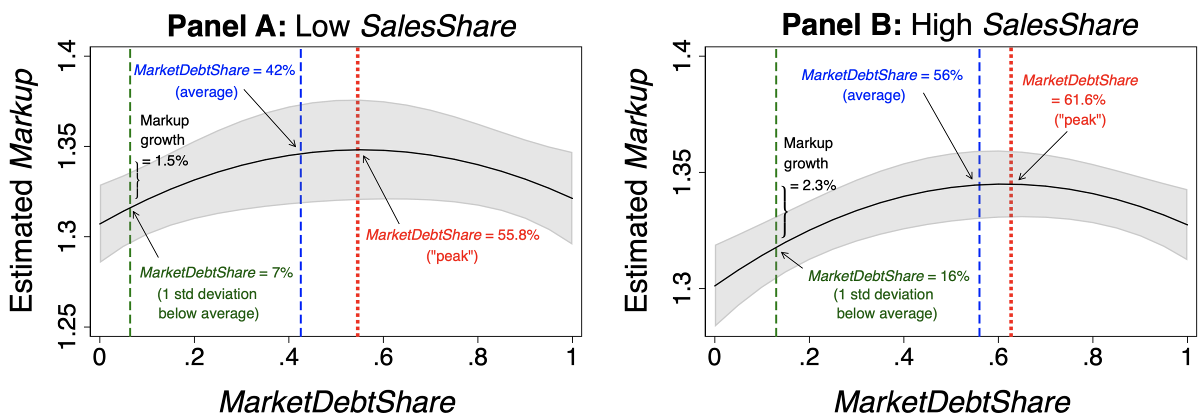
Note: This figure presents the estimated quadratic, hump-shaped relationship between $\mathcal{M}$ and $MarketDebtShare$ for firms below (**Panel (A)**) and above (**Panel (B)**) the median (firm-level), time-series average $SGAX$ ratio. For each group, $Leverage$ is evaluated at its mean value. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. The **gray** area represents 95% confidence intervals. In both panels, standard errors are clustered by firm and year.

Figure A.6: (Robustness) Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SGAX$



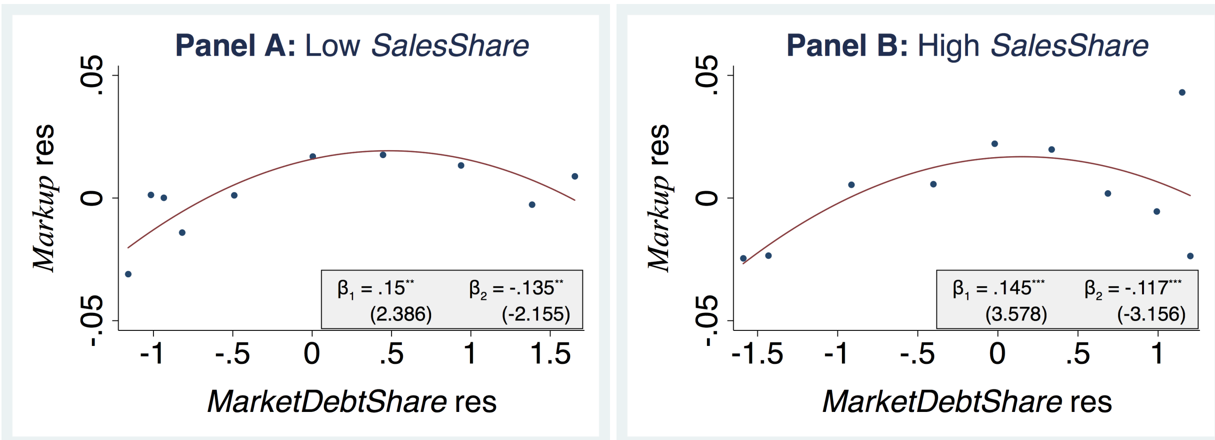
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. Firms are sorted into two groups based on their firm-level, time-series average $SGAX$ ratio. Firms below and above the median of this time-series average characterize the two separate groups. The variable markup $\mathcal{M}$ and $MarketDebtShare$ are residualized from $Leverage$ for firms *below* (**Panel (A)**) and *above* (**Panel (B)**) the median of this time-series average, as well as (5-digit) NAICS industry fixed effects, year fixed effects, and the following additional firm-level controls: lagged markup $\mathcal{M}$, size, age, sales growth, market-to-book ratio, cash, tangibility, profitability, interest rate coverage ratio, a dividend payout dummy, the Whited and Wu (2006) index, the Bodnaruk et al. (2015) index, as well as S&P credit rating binned fixed effects. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. For each group, $MarketDebtShare$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals for each group. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.7: Estimated Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SalesShare$



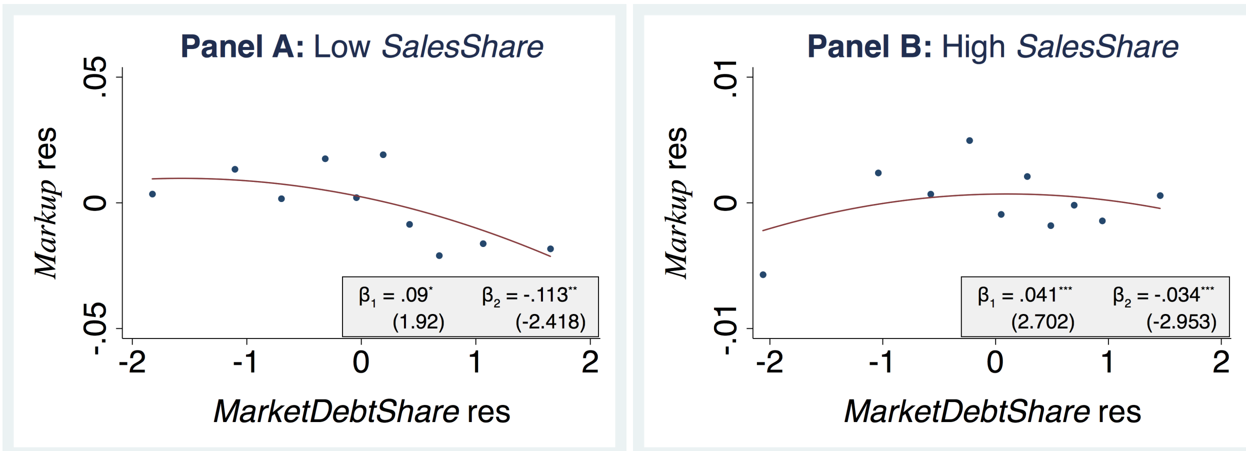
Note: This figure presents the estimated quadratic, hump-shaped relationship between $\mathcal{M}$ and $MarketDebtShare$ for firms sorted into two groups based on the median $SalesShare$ by year. For each group, $Leverage$ is evaluated at its mean value. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SalesShare$ is sales over total industry sales. The **gray** area represents 95% confidence intervals. In both panels, standard errors are clustered by firm and year.

Figure A.8: Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SalesShare$



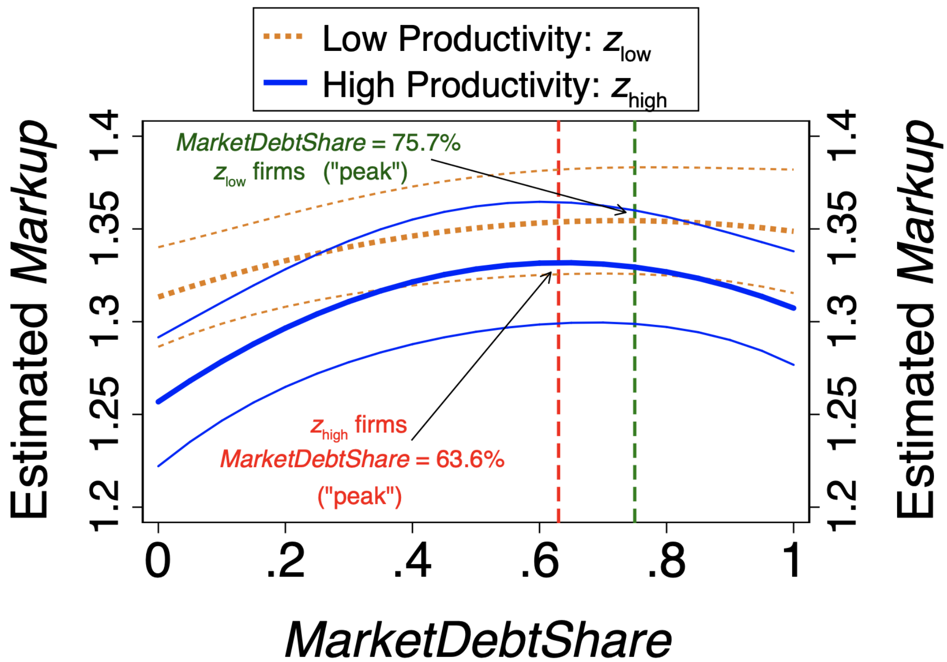
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. Firms are sorted into two groups based on the median $SalesShare$ by year. Firms below and above the median $SalesShare$ characterize the two separate groups. The variable markup $\mathcal{M}$ and $MarketDebtShare$ are residualized from $Leverage$. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SalesShare$ is sales over total industry sales. For each group, $MarketDebtShare$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals for each group. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.9: (Robustness) Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SalesShare$



Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. Firms are sorted into two groups based on the median $SalesShare$ by year. Firms below and above the median $SalesShare$ characterize the two separate groups. The variable markup $\mathcal{M}$ and $MarketDebtShare$ are residualized from $Leverage$, as well as (5-digit) NAICS industry fixed effects, year fixed effects, and the following additional firm-level controls: lagged markup $\mathcal{M}$, size, age, sales growth, market-to-book ratio, cash, tangibility, profitability, interest rate coverage ratio, a dividend payout dummy, the Whited and Wu (2006) index, the Bodnaruk et al. (2015) index, as well as S&P credit rating binned fixed effects. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over COGS. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SalesShare$ is sales over total industry sales. For each group, $MarketDebtShare$ residuals are normalized to have zero mean and unit variance. Residualized variables are grouped into 10 equal-sized bins. The **red curve** is the best quadratic fit, which is constructed using an OLS regression of $\mathcal{M}$ residuals on $MarketDebtShare$ and $MarketDebtShare^2$ residuals for each group. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

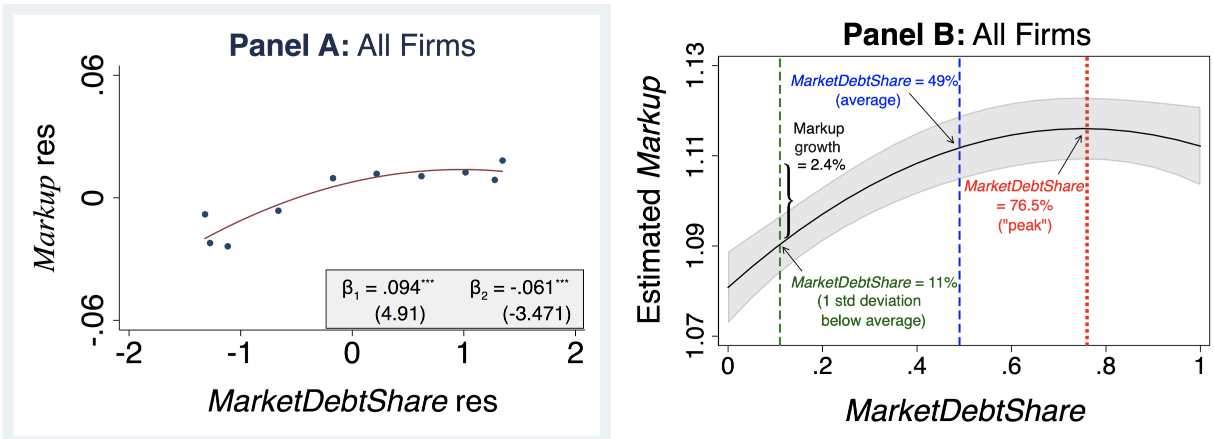
Figure A.10: Relationship between $\mathcal{M}$ and $MarketDebtShare$ - (z_{low} vs. z_{high})



Note: This figure presents the estimated quadratic, hump-shaped relationship between $\mathcal{M}$ and $MarketDebtShare$ for firms sorted into two groups based on the median, time-series average of TFP measures. Firms below and above the median are z_{low}- and z_{high}-firms, respectively. TFP is obtained from the output of the method used to estimate $\mathcal{M}$ (see **Section A.5** in this Appendix). For each group, both $Leverage$ and $SGAX$ are evaluated at their mean values. The gray area represents 95% confidence intervals. In both panels, standard errors are clustered by firm and year.

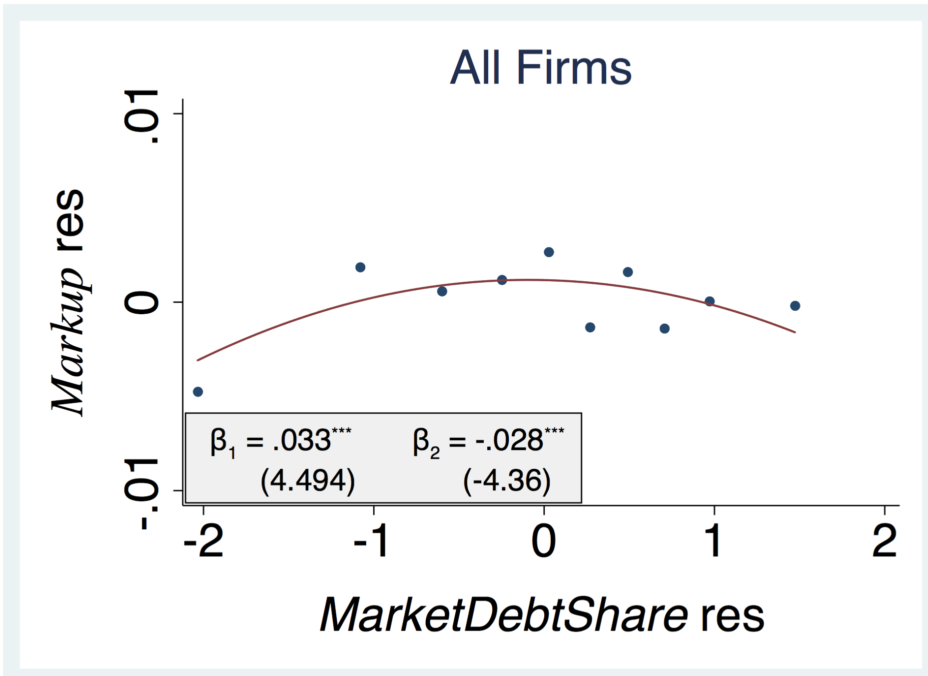
Estimation of Markups $\mathcal{M}$ with (COGS + SGA) as Variable Costs

Figure A.11: Relationship between $\mathcal{M}$ and $MarketDebtShare$



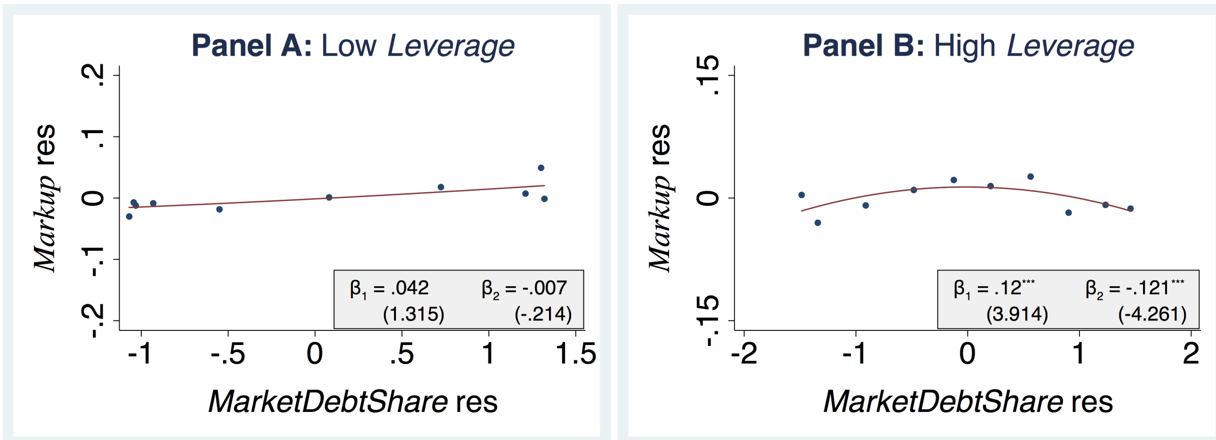
Note: The figures presented here are obtained in a similar manner to those shown in **Figure 1.2**, but with the inclusion of SGA expenses in total variable costs. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. $SGAX$ is SGA expeneses over sales. In **Panel (B)** the gray area represents 95% confidence intervals. In both panels, standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.12: (Robustness) Relationship between $\mathcal{M}$ and $MarketDebtShare$



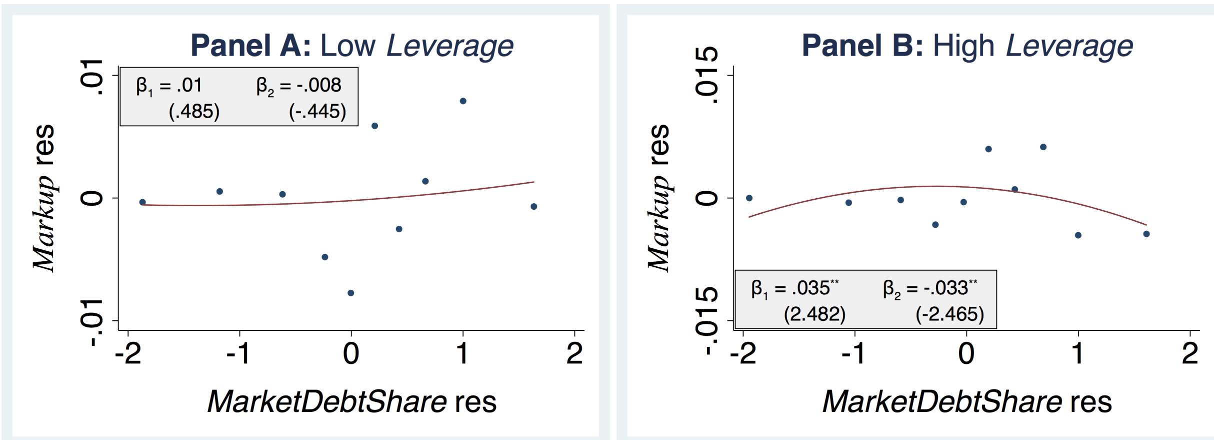
Note: This figure presents a non-parametric estimate of the CEF using a binned scatterplot, along with a quadratic parametric estimate. These estimates are obtained in a similar manner to those shown in **Figure A.2**, but with the inclusion of SGA expenses in total variable costs. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. $SGAX$ is SGA expeneses over sales. The legend box (in gray) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.13: Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $Leverage$



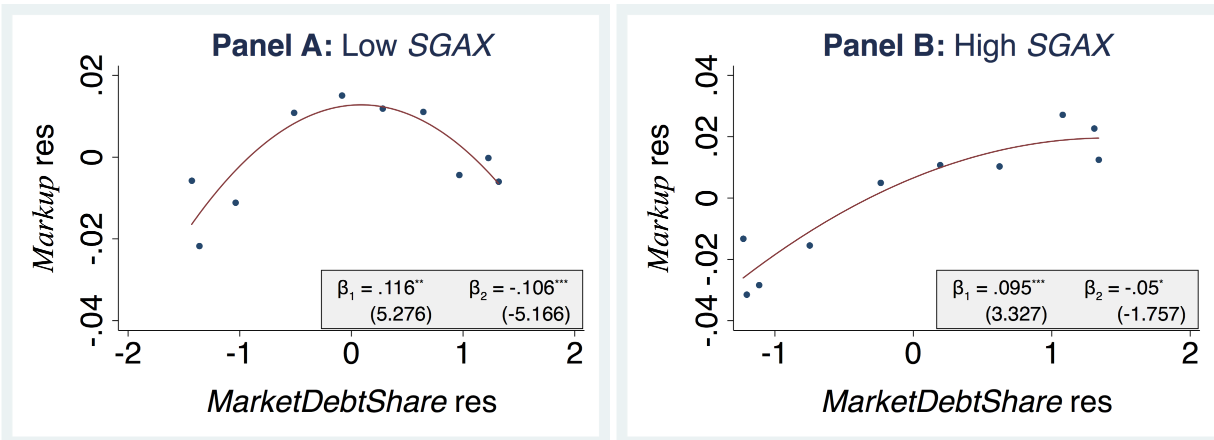
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. These estimates are obtained in a similar manner to those shown in **Figure 1.3**, but with the inclusion of SGA expenses in total variable costs. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expeneses over sales. The legend box (in gray) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.14: (Robustness) Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $Leverage$



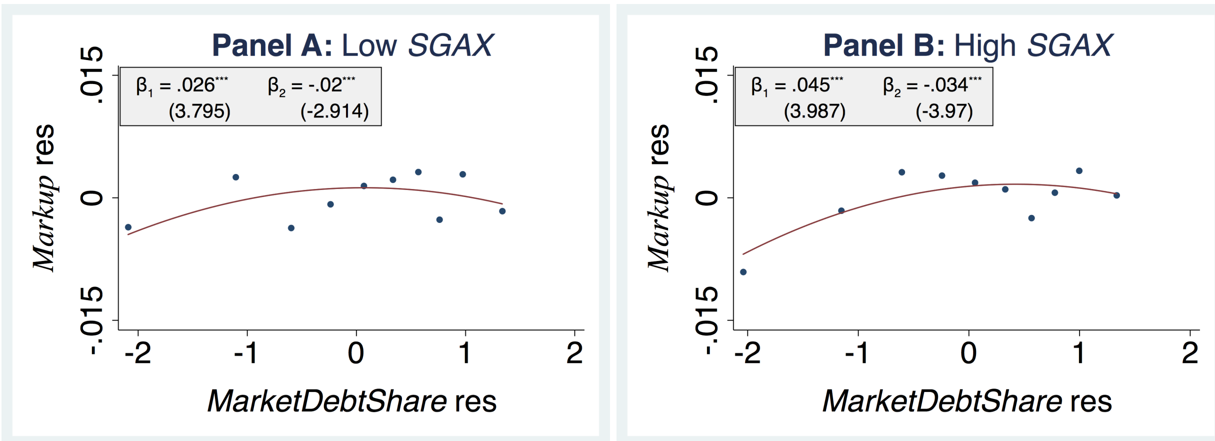
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. These estimates are obtained in a similar manner to those shown in **Figure A.4**, but with the inclusion of SGA expenses in total variable costs. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expeneses over sales. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.15: Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SGAX$



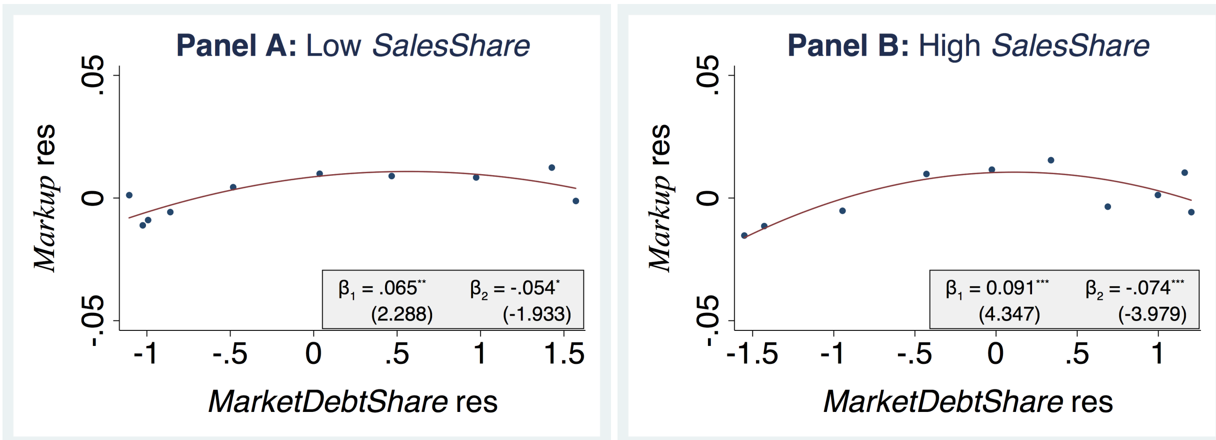
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. These estimates are obtained in a similar manner to those shown in **Figure 1.4**, but with the inclusion of SGA expenses in total variable costs. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. *Leverage* is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expeneses over sales. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.16: (Robustness) Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SGAX$



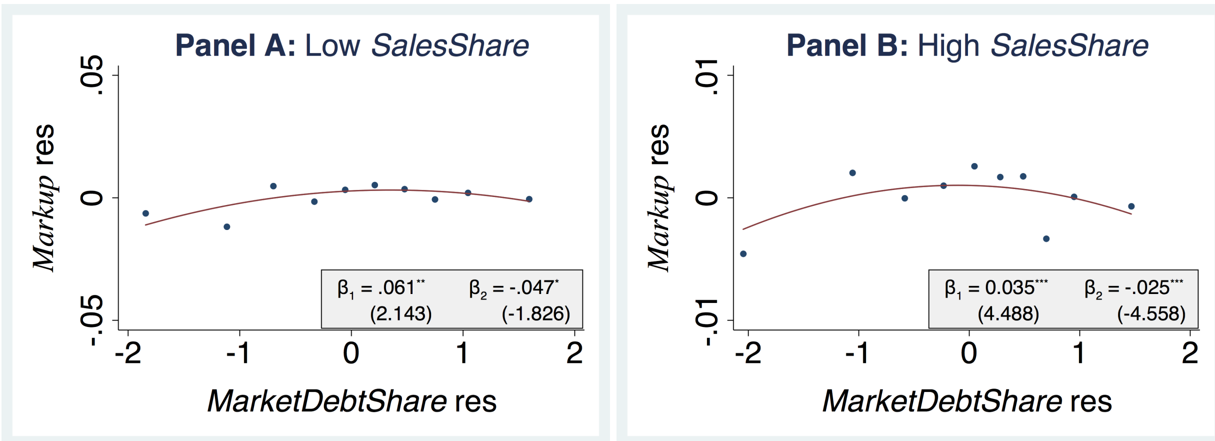
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. These estimates are obtained in a similar manner to those shown in **Figure A.6**, but with the inclusion of SGA expenses in total variable costs. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expeneses over sales. The legend box (in **gray**) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.17: Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SalesShare$



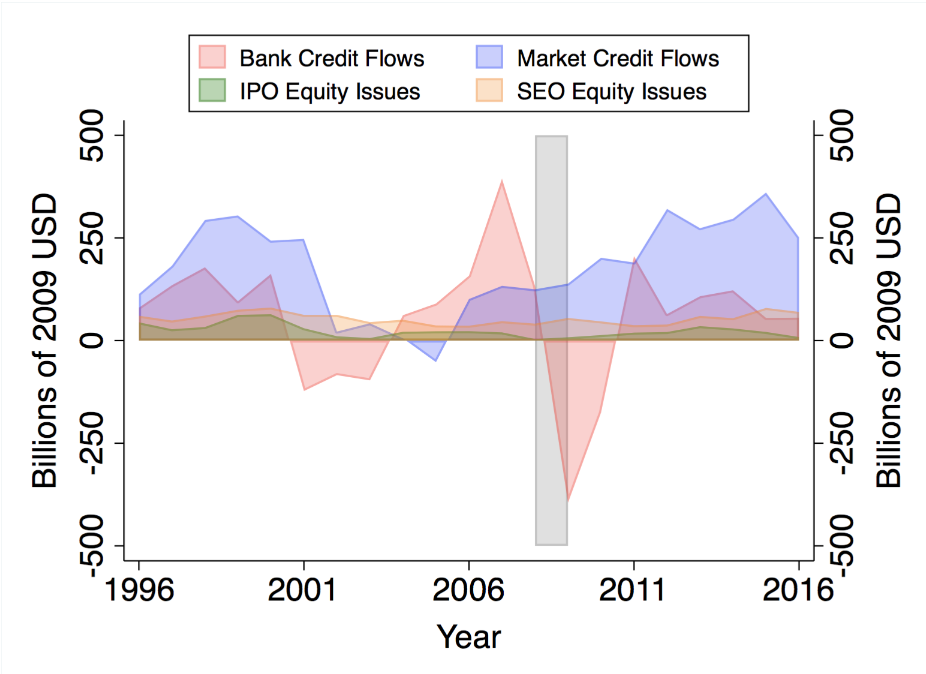
Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. These estimates are obtained in a similar manner to those shown in **Figure A.8**, but with the inclusion of SGA expenses in total variable costs. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. *Leverage* is the sum of bank and market debt over the market value of assets. $SalesShare$ is sales over total industry sales. The legend box (in gray) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.18: (Robustness) Relationship between $\mathcal{M}$ and $MarketDebtShare$ - "Low" and "High" $SalesShare$



Note: This figure presents non-parametric estimates of CEFs using binned scatterplots, along with quadratic parametric estimates. These estimates are obtained in a similar manner to those shown in **Figure A.9**, but with the inclusion of SGA expenses in total variable costs. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. *Leverage* is the sum of bank and market debt over the market value of assets. $SalesShare$ is sales over total industry sales. The legend box (in gray) shows the point estimates for $MarketDebtShare$ (β_1) and $MarketDebtShare^2$ (β_2), with t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.19: U.S. Flows in External Equity and Debt Financing



Source: FRB Flows of Funds, Table F103; FRED
Note: Bank credit is the sum of bank loans not elsewhere classified (n.e.c.) and other loans. Market credit is the sum of corporate bonds and commercial paper. Initial public offering (IPO) issuances includes new equity issuance by companies that were not previously publicly traded. The offering prices of these securities are determined prior to the listing. Seasoned equity offering (SEO) issuances includes new equity issuance by existing publicly traded companies. Financial crisis years (2008-09) are represented by the gray area.

A.2 Additional Tables

Estimation of Markups $\mathcal{M}$ with COGS as Variable Costs

Table A.1: (Robustness) Regressions Associated with Binned Scatterplots - $\mathcal{M}$ and $MarketDebtShare$

VARIABLES	Variable markup $\mathcal{M}$						
	(1) **All** ***Firms***	(2) Low *Leverage*	(3) **High** ***Leverage***	(4) **Low** ***SGAX***	(5) **High** ***SGAX***	(6) **Low** ***SalesShare***	(7) **High** ***SalesShare***
$\widehat{\beta}_1 : MarketDebtShare$	0.044***	0.023	0.076**	0.062***	0.070***	0.090*	0.041**
	(2.995)	(0.709)	(2.448)	(3.360)	(2.701)	(1.920)	(2.702)
$\widehat{\beta}_2 : MarketDebtShare^2$	-0.043***	-0.026	-0.065**	-0.050***	-0.056***	-0.113**	-0.034***
	(-3.404)	(-0.872)	(-2.505)	(-3.234)	(-2.809)	(-2.418)	(-2.953)
"Peak" share : $\frac{\widehat{\beta_1}}{(2\times\widehat{\beta_2})}$	**.515*****	.446**	**.587*****	**.618*****	**.638*****	**.397*****	**.599*****
	(8.457)	(1.986)	(7.148)	(10.898)	(11.704)	(6.607)	(8.881)
Wald test of Equality in $\frac{\widehat{\beta_1}}{(2\times\widehat{\beta_2})}$				2.85*		3.61*	
χ^2 (p-value)				(0.089)		(0.057)	
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,510	983	2,556	5,121	3,389	1,208	6,278
R^2	0.885	0.939	0.862	0.796	0.841	0.774	0.921

Note: This table presents regression estimates for the quadratic specifications associated with **Figures A.2**, **A.4**, **A.6**, and **A.9**. Results shown in Columns (1)-(7) are estimated with the inclusion of (5-digit) NAICS industry fixed effects, year fixed effects, as well as the following additional firm-level controls: lagged markup $\mathcal{M}$, size, age, sales growth, market-to-book ratio, cash, tangibility, profitability, interest rate coverage ratio, a dividend payout dummy, the Whited and Wu (2006) index, the Bodnaruk et al. (2015) index, and S&P credit rating binned fixed effects. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over SGA expenses. $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. $SalesShare$ is sales over total industry sales. t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Regressions in Table 1.6 from 1992 to 2007

VARIABLES	Variable markup $\mathcal{M}$				
	(1) **All** ***Firms***	(2) Low *Leverage*	(3) **High** ***Leverage***	(4) **Low** ***SGAX***	(5) **High** ***SGAX***
$\widehat{\beta}_1 : MarketDebtShare$	0.133***	-0.002	0.151*	0.145***	0.175***
	(3.623)	(-0.025)	(1.915)	(3.345)	(2.880)
$\widehat{\beta}_2 : MarketDebtShare^2$	-0.109***	0.036	-0.164**	-0.121***	-0.126**
	(-2.925)	(0.392)	(-2.221)	(-2.995)	(-2.076)
"Peak" share : $\frac{\widehat{\beta}_1}{(2\times\widehat{\beta}_2)}$	**.61***	.031	**.461***	**.598***	**.695***
	(9.341)	(.027)	(6.855)	(9.322)	(5.802)
Wald test of Equality in $\frac{\widehat{\beta}_1}{(2\times\widehat{\beta}_2)}$				3.64**	
χ^2 (p-value)				(0.054)	
Firm Controls	No	No	No	No	No
Industry FE	No	No	No	No	No
Year FE	No	No	No	No	No
Observations	13,821	3,479	3,431	6,917	6,904
R^2	0.164	0.007	0.029	0.025	0.017

Note: This table presents regression estimates associated with the same specifications from **Table 1.6**, but over the sub-sample period from 1992 to 2007, which is the period used to calibrate key parameters in the model. t-statistics of point estimates are in parentheses. Standard errors are clustered by firm and year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Estimation of Markups $\mathcal{M}$ with (COGS + SGA) as Variable Costs

Table A.3: Regressions Associated with Binned Scatterplots - $\mathcal{M}$ and $MarketDebtShare$

VARIABLES	Variable markup $\mathcal{M}$						
	(1) **All** ***Firms***	(2) Low *Leverage*	(3) **High** ***Leverage***	(4) **Low** ***SGAX***	(5) **High** ***SGAX***	(6) **Low** ***SalesShare***	(7) **High** ***SalesShare***
$\widehat{\beta}_1 : MarketDebtShare$	0.094***	0.042	0.120***	0.116***	0.095***	0.065**	0.091***
	(4.910)	(1.315)	(3.914)	(5.276)	(3.327)	(2.288)	(4.347)
$\widehat{\beta}_2 : MarketDebtShare^2$	-0.061***	-0.007	-0.121***	-0.106***	-0.050*	-0.054*	-0.074***
	(-3.471)	(-0.214)	(-4.261)	(-5.166)	(-1.757)	(-1.933)	(-3.979)
"Peak" share : $\frac{\widehat{\beta_1}}{(2\times\widehat{\beta_2})}$	**.765*****	3.086	**.497*****	**.548*****	**.954*****	**.604*****	**.615*****
	(8.597)	(.253)	(12.07)	(19.065)	(3.339)	(5.859)	(13.86)
Wald test of Equality in $\frac{\widehat{\beta_1}}{(2\times\widehat{\beta_2})}$				4.35**		3.92*	
χ^2 (p-value)				(0.036)		(0.048)	
Firm Controls	No	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No	No
Year FE	No	No	No	No	No	No	No
Observations	22,218	5,552	5,512	11,120	11,098	8,584	14,081
R^2	0.059	0.070	0.010	0.048	0.021	0.010	0.057

Note: This table provides regression estimates for the quadratic specifications associated with **Figures A.11**, **A.13**, **A.15**, and **A.17**. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. $SalesShare$ is sales over total industry sales. t-statistics in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Regressions in Table A.3 from 1992 to 2007

VARIABLES	Variable markup $\mathcal{M}$						
	(1) **All** ***Firms***	(2) Low *Leverage*	(3) **High** ***Leverage***	(4) **Low** ***SGAX***	(5) **High** ***SGAX***	(6) **Low** ***SalesShare***	(7) **High** ***SalesShare***
$\widehat{\beta}_1 : MarketDebtShare$	0.076***	0.047	0.096**	0.087***	0.090***	0.072*	0.065***
	(3.651)	(1.298)	(2.652)	(3.611)	(2.931)	(2.053)	(2.991)
$\widehat{\beta}_2 : MarketDebtShare^2$	-0.057***	-0.026	-0.110***	-0.080***	-0.065**	-0.075**	-0.058**
	(-2.909)	(-0.748)	(-3.346)	(-3.534)	(-2.221)	(-2.324)	(-2.854)
"Peak" share : $\frac{\widehat{\beta}_1}{(2\times\widehat{\beta}_2)}$	**.672***	.902	**.437***	**.542***	**.697***	**.484***	**.564***
	(9.594)	(1.629)	(7.885)	(12.811)	(6.732)	(7.477)	(10.714)
Wald test of Equality in $\frac{\widehat{\beta}_1}{(2\times\widehat{\beta}_2)}$				12.60*		2.85*	
χ^2 (*p*-value)				(0.000)		(0.089)	
Firm Controls	No	No	No	No	No	No	No
Industry FE	No	No	No	No	No	No	No
Year FE	No	No	No	No	No	No	No
Observations	14,357	3,605	3,557	7,180	7,177	5,341	9,342
R^2	0.057	0.052	0.009	0.046	0.013	0.010	0.055

Note: This table presents regression estimates associated with the same specifications from **Table A.3**, but over the sub-sample period from 1992 to 2007, which is the period used to calibrate key parameters in the model. *t*-statistics of point estimates are in parentheses. Standard errors are clustered by firm and year. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: (Robustness) Regressions Associated with Binned Scatterplots - $\mathcal{M}$ and $MarketDebtShare$

VARIABLES	Variable markup $\mathcal{M}$						
	(1) **All** ***Firms***	(2) Low *Leverage*	(3) **High** ***Leverage***	(4) **Low** ***SGAX***	(5) **High** ***SGAX***	(6) **Low** ***SalesShare***	(7) **High** ***SalesShare***
$\widehat{\beta}_1 : MarketDebtShare$	0.033***	0.010	0.035**	0.026**	0.045***	0.061**	0.035***
	(4.494)	(0.485)	(2.482)	(3.795)	(3.987)	(2.143)	(4.488)
$\widehat{\beta}_2 : MarketDebtShare^2$	-0.028***	-0.008	-0.033**	-0.020**	-0.034***	-0.047*	-0.025***
	(-4.360)	(-0.445)	(-2.465)	(-2.914)	(-3.970)	(-1.826)	(-4.558)
"Peak" share : $\frac{\widehat{\beta_1}}{(2\times\widehat{\beta_2})}$	**.592*****	.667	**.529*****	**.651*****	**.656*****	**.638*****	**.690*****
	(11.589)	(1.534)	(6.662)	(7.796)	(10.479)	(6.212)	(14.616)
Wald test of Equality in $\frac{\widehat{\beta_1}}{(2\times\widehat{\beta_2})}$				2.98*		2.76*	
χ^2 (p-value)				(0.082)		(0.092)	
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,586	955	2,597	5,270	3,316	1,217	7,520
R^2	0.820	0.868	0.805	0.753	0.792	0.697	0.865

Note: This table provides regression estimates for the quadratic specifications associated with **Figures A.12**, **A.14**, **A.16**, and **A.18**. Results shown in Columns (1)-(7) are estimated with the inclusion of (5-digit) NAICS industry fixed effects, year fixed effects, and the following additional firm-level controls: lagged markup $\mathcal{M}$, size, age, sales growth, market-to-book ratio, cash, tangibility, profitability, interest rate coverage ratio, interest rate coverage ratio, a dividend payout dummy, the Whited and Wu (2006) index, the Bodnaruk et al. (2015) index, as well as S&P credit rating binned fixed effects. The variable markup $\mathcal{M}$ is estimated using the structural procedure in **Appendix A.4**, giving a scaled ratio of sales over (COGS + SGA expenses). $MarketDebtShare$ is market debt over the sum of bank and market debt. $Leverage$ is the sum of bank and market debt over the market value of assets. $SGAX$ is SGA expenses over sales. $SalesShare$ is sales over total industry sales. t-statistics in parentheses. Standard errors are clustered by firm and year.

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

A.3 Description of Variables

I follow De Loecker and Eeckhout (2017) and use historical, 5-digit NAICS codes to classify industries. The NAICS system offers several advantages over the Standard Industrial Classification (SIC) system. For example, NAICS codes are based on a consistent, economic concept, and group together establishments that use the same or similar, production processes. Under the SIC system, some establishments are classified according to production processes, while others are classified using different criteria, which create inconsistent groupings across firms. Economically, product market industries should be "sufficiently" fine enough so that the customer market interpretation is admissible. This justifies the use of 5-digit versus 3- or 4-digit codes.

A.4 Estimation of Variable Markups

Variable markups are estimated using the approach introduced in Hall (1988). This approach has been implemented in De Loecker and Eeckhout (2017) and Traina (2018) by making use of accounting data extracted from Compustat to estimate the ratio of product price to marginal cost.

This structural framework rests on the assumption firms minimize total costs, and the existence of at least one variable input to production, free of adjustment costs. This structural procedure does not require the econometrician to posit a demand system, or a specific market structure. The wedge between a variable input's revenue share and its output elasticity is the estimate of a firm's variable markup.

I now describe the structural procedure by borrowing heavily from De Loecker and Eeckhout (2017) and Traina (2018).[1] Let J denote the number of industries, N the number of firms, and $i = 1, 2, 3, ..., N$ the index for each firm. Time is indexed by t. De Loecker and Eeckhout (2017) obtain a simple expression for firm i's markup at time t via this cost minimization problem:

$$\mathcal{M}_{i,j,t} = \alpha_j^v \left(\frac{p_{i,j,t} q_{i,j,t}}{p_{i,j,t}^v v_{i,j,t}} \right)$$

with α_j^v denoting the output elasticity of variable input v in industry j, $p_{i,j,t} q_{i,j,t}$ denoting output in terms of sales, and $p_{i,j,t}^v v_{i,j,t}$ denoting the total variable cost of production. Here, the industry-specific elasticity is interpreted as firms within an industry having access to the same technology, though differing in optimally chosen inputs and productivity.

Total sales (SALE) and total variable production costs are measured directly from accounting data in Compustat. Throughout this paper, I follow De Loecker and Eeckhout (2017) and measure total variable production costs by using Compustat's cost of goods sold (COGS). That said, Traina (2018) contends selling, general, and administrative (SGA) ex-

[1] I thank James Traina for making his estimation code and dataset available to me.

penses, which include a firm's non-production costs, such as advertising, marketing, and more generally, overhead costs, are potentially variable. As a result, I combine both COGS and SGA expenses in the calculation of variable costs as a robustness check. Descriptive statistics for both sets of variable markups are shown in **Table 1.5**.

In order to recover variable markup $\mathcal{M}$, an estimate of the output elasticity α_j^v is required. The markup equation is an optimality condition, and will hold for any variable input, though an unbiased estimate of that variable input's output elasticity is needed to properly estimate $\mathcal{M}$. For a given industry j, I estimate the Cobb-Douglas production function

$$\log\left(q_{i,j,t}\right) = \alpha_j^v \log\left(v_{i,j,t}\right) + \alpha_j^k \log\left(k_{i,j,t-1}\right) + \log\left(\omega_{i,j,t}\right) + \epsilon_{i,j,t} \tag{A.1}$$

with $\log\left(q_{i,j,t}\right)$ denoting the log of firm sales, $\log\left(v_{i,j,t}\right)$ denoting the log of variable costs, $\log\left(k_{i,j,t-1}\right)$ denoting the log of the lagged capital stock, and $\log\left(\omega_{i,j,t}\right)$ denoting log productivity.

Firm sales (SALE) and variable costs (COGS) are deflated by using the NIPA Table 1.1.9, GDP deflator (line 1).[2] I follow the production estimation literature, and construct a measure of physical capital with the use of a perpetual inventory method. I achieve this by initializing the capital stock with the first available entry of *gross* property, plant, and equipment (PPEGT) from Compustat. I then use the law of motion for capital $k_{i,j,t} = \left(1-\delta^k\right) k_{i,j,t-1} + i_{i,j,t}$, and iterate forward in order to compute net investment $i_{i,j,t} - \delta^k k_{i,j,t-1}$ with changes in Compustat's *net* property, plant, and equipment (PPENT). Finally, a measure of the real capital stock is obtained by deflating net investment with the non-residential fixed investment good deflator (NIPA Table 1.1.9, line 9).[3]

In order to estimate equation (A.1), particularly coefficient α_j^v, I control for the simultaneity and selection bias inherently present in the estimation using a control function approach. I combine this with an $AR\left(1\right)$ process specification for log productivity,

$$\begin{aligned} \log\left(\omega_{i,j,t}\right) &= \rho_{i,j} \log\left(\omega_{i,j,t-1}\right) + \xi_{i,j,t} \\ \xi_{i,j,t} &\sim WhiteNoise\left(0, \sigma^2_{\xi_{i,j}}\right) \end{aligned} \tag{A.2}$$

This approach relies on two-stages. In the first stage, measurement error and unanticipated shocks to sales are purged by calculating a prediction from a (sales-weighted) regression of sales on the variable input and capital, with firm and year fixed effects:

$$\log\left(q_{i,j,t}\right) = \alpha_j^v \log\left(v_{i,j,t}\right) + \alpha_j^k \log\left(k_{i,j,t-1}\right) + \mu_i + \gamma_t + \epsilon_{i,j,t}$$

[2] See BEA, National Income and Product Accounts.

[3] Although PPEGT is a measure of the book value of capital stock, I construct my own measure of capital using a perpetual inventory method consistent with De Loecker and Eeckhout (2017) and Traina (2018). Any missing observations are replaced with a linear interpolation of their neighboring values. As an alternative, I consider replacing any missing observations with their most recently observed value. Results do not depend on a specific interpolation scheme.

In the second stage, predicted sales are used to obtain implied productivity as a function of the elasticity parameter vector $\alpha_j = \left(\alpha_j^v, \alpha_j^k\right)$. This function, $\omega_{i,j,t}\left(\alpha_j\right)$, is projected onto its lag $\omega_{i,j,t-1}\left(\alpha_j\right)$, which enables recovery of the innovation function $\xi_{i,j,t}\left(\alpha_j\right)$. I then use $\xi_{i,j,t}\left(\alpha_j\right)$ to identify the industry-specific output elasticity α_j^v via an assumed moment restriction:

$$\mathbb{E}\left[\xi_{i,j,t}\left(\alpha_j^v, \alpha_j^k\right) \cdot \begin{pmatrix} v_{i,j,t-1} \\ k_{i,j,t-1} \end{pmatrix}\right] = 0$$

The orthogonality condition above is valid under the assumption capital and the variable input respond to productivity shocks, though their lags do not. Additionally, lagged variable input must be correlated with the current variable input, which is guaranteed through persistence in $\log\left(\omega_{i,j,t}\right)$.

Firm-level variable markups are then measured using the estimate of α_j^v:

$$\mathcal{M}_{i,j,t} = \widehat{\alpha_j^v}\left(\frac{p_{i,j,t}q_{i,j,t}}{p_{i,j,t}^v v_{i,j,t}}\right) \tag{A.3}$$

A.5 Calibration Procedures

The structural estimation procedure described in **Section A.4** provides industry-level output elasticities $(\widehat{\alpha_j^v})$, firm-level variable markups $(\mathcal{M}_{i,j,t})$, and firm-level productivity parameters $(\widehat{\rho_{i,j}}, \widehat{\sigma_{\xi_{i,j}}^2})$. To calibrate the variable factor share $(1-\alpha)$, I use a cross-sectional median output elasticity, which gives a value of $\widehat{\alpha_j^v} \equiv (1-\alpha) = 0.93$

Table A.6: Descriptive Statistics - Output Elasticity of Variable Factor v

	Mean	**SD**	**p5**	**p25**	**p50**	**p75**	**p95**	**N**
$\widehat{\alpha_j^v}$	0.871	0.135	0.570	0.823	**0.930**	0.960	1.009	356

Note: The industry classification is 5-digit NAICS.

To calibrate a set of idiosyncratic productivity parameters $(z_1, z_2, \lambda_1$, and $\lambda_2)$, I proceed as follows: First, I use both the cross-sectional median estimate for the persistence parameter $\widehat{\rho_{i,j}}$ and volatility parameter $\sqrt{\widehat{\sigma_{\xi_{i,j}}^2}}$. This yields values $\widehat{\rho} = 0.986$ and $\sqrt{\widehat{\sigma_\xi^2}} = 0.038$. I then approximate the "median" idiosyncratic $AR(1)$ process given by

$$\log(\omega_t) = \widehat{\rho}\,\log(\omega_{t-1}) + \xi_t$$
$$\xi_t \sim WhiteNoise\left(0, \widehat{\sigma_\xi^2}\right)$$

with a two-state Markov chain using the method in Rouwenhorst (1995). This method is especially suited when approximating highly persistent processes. Moreover, it generates accurate model solutions. This procedure yields two discrete points, $Z_1 = -0.2279$ and $Z_2 = 0.2279$, with conditional probabilities $\mathbb{P}\left[Z_1 \middle| Z_1\right] = \mathbb{P}\left[Z_2 \middle| Z_2\right] = 0.993$. The model's two-state Poisson process parameters are then given by

$$z_1 = exp^{Z_1} = 0.7962,\ z_2 = exp^{Z_2} = 1.256$$
$$\lambda_n = -\log\left(\mathbb{P}\left[Z_n \middle| Z_n\right]\right) = 0.007,\ \text{for } n = 1, 2$$

Table A.7: Firm-Level $AR(1)$ Productivity Parameters

	Mean	**SD**	**p5**	**p25**	**p50**	**p75**	**p95**	**N**
$\widehat{\rho_{i,j}}$	0.974	0.018	0.948	0.984	**0.986**	0.994	0.997	7,044
$\widehat{\sigma_{\xi,i,j}}$	0.036	0.021	0.016	0.023	**0.038**	0.049	0.075	7,044

Note: The industry classification is 5-digit NAICS.

For each state $s \in \{\mu, k, b, m, z\}$, I calibrate "shape" and "scale" parameters (ξ_s, σ_s) of the marginal, generalized Pareto distributions characterizing the joint entry distribution $\boldsymbol{\Upsilon}(\mu, k, b, m, z)$ as follows:

I start by fitting a generalized Pareto distribution (GPD) with empirical counterparts for customer base μ, capital k, bank debt b, market debt m, and idiosyncratic productivity z. In the data, μ is SGA expenses, k is the book value of assets (2009 USD mill.), b is $BankDebt$, m is $MarketDebt$ (see **Table 1.2**), and z is implied productivity from the structural estimation described in **Appendix A.4**. For each firm characteristic in CIQ and Compustat, I use the first, non-missing observation beginning in 1992. Within the context of my model, I interpret this as an "IPO" observation. For each characteristic's GPD, I truncate its support so that it matches both numerical lower and upper bounds of its model analog (see **Online Appendix**).

A.6 Derivations and Proofs

Proposition 1 (Lending menu): The lending menu $\mathcal{L}(\mu, k, b, m, z)$ is non-empty and compact for all feasible states (μ, k, b, m, z). Moreover, $\mathcal{L}(\mu, k, b, m, z)$ can be partitioned into two non-empty, compact, and convex subsets $\mathcal{L}_K(\mu, k, b, m, z)$ and $\mathcal{L}_R(\mu, k, b, m, z)$, such that:

- *The lending terms* (D_b, D_m) satisfy $\frac{D_b}{\chi} \geq \frac{D_m}{1-\chi}$, *if and only if,* $(l_b, l_m) \in \mathcal{L}_R(\mu, k, b, m, z)$*;*
- *The lending terms* (D_b, D_m) satisfy $\frac{D_b}{\chi} < \frac{D_m}{1-\chi}$, *if and only if,* $(l_b, l_m) \in \mathcal{L}_K(\mu, k, b, m, z)$

with $(1 - \chi) \in [0, 1)$ representing the fraction of $EBIAT$ that is lost by the firm's shareholders in liquidation.

Proof. This proposition is a straightforward extension of Proposition 2 in Crouzet (2017) applied to an economy with a customer market and imperfect competition. The proof is neglected to save space. □

Appendix B

Appendix to Chapter 2

B.1 Construction of Real GDP-Tracking News via Replicating Portfolios

The error term in (2.2) can be characterized as a function of a series of monetary and non-monetary shocks hitting the aggregate economy. We denote monetary shocks by $\epsilon_{mp,t}$ and non-monetary shocks, such as productivity or oil price shocks, by $\epsilon_{-mp,t}$.

$$u_t = f(\epsilon_{mp,t}, \epsilon_{-mp,t}) \tag{B.1}$$

In practice, non-monetary news may have systematic effects on the returns of various asset classes. For example, stock returns can rise in response to high productivity growth, while an oil price shock could have negative effects on the stock price of firms heavily relying on oil inputs.

To identify the loadings $\{\gamma_i\}$ in (2.2), we require that real GDP-tracking news, constructed via replicating portfolios based on underlying monetary and non-monetary shocks, have close to equivalent loadings. Formally, this can be shown as follows: we first construct two separate real GDP-tracking portfolios, one based on monetary news, the other on non-monetary news. Taking the conditional expectation of real GDP growth with respect to monetary and non-monetary news, we can use the use the portfolio of base assets with weights $\{\gamma_i\}$ and $\{\alpha_i\}$, respectively (see (B.2) and (B.3)):

$$E[\Delta y_{t+k}|\epsilon_{mp,t}] = \sum_{i=1}^{j} \gamma_i R_{i,t+k} \tag{B.2}$$

$$E[\Delta y_{t+k}|\epsilon_{-mp,t}] = \sum_{i=1}^{j} \alpha_i R_{i,t+k} \tag{B.3}$$

Now, assume u_t incorporates monetary news with probability p and non-monetary news with probability $1 - p$. Taking the unconditional expectation of real GDP growth in (B.4) yields:

$$E[\Delta y_{t+k}] = p \times \sum_{i=1}^{j} \gamma_i R_{i,t+k} + (1 - p) \times \sum_{i=1}^{j} \alpha_i R_{i,t+k} \tag{B.4}$$

The portfolio weights estimated (unconditionally) in (2.2) are an unbiased estimator of γ_i if and only if $\alpha_i = \gamma_i$. In other words, the covariance between asset returns and real GDP growth *conditional* on monetary and non-monetary shocks are equal. This is stated formally below:

$$\alpha_i = \gamma_i \equiv cov(R_{i,t+k}, E[\Delta y_{t+k}|\epsilon_{mp,t}]) = cov(R_{i,t+k}, E[\Delta y_{t+k}|\epsilon_{-mp,t}]) \tag{B.5}$$

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