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THREE EMPIRICAL ESSAYS IN FINANCIAL ECONOMICS
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THREE EMPIRICAL ESSAYS IN FINANCIAL ECONOMICS AND INTERNATIONAL FINANCE

By

Marek Kolar

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ABSTRACT

THREE EMPIRICAL ESSAYS IN FINANCIAL ECONOMICS AND INTERNATIONAL FINANCE

By

Marek Kolar

In the first chapter, "Credit Reallocation", we inquire into the existence of a process of inter-firm credit reallocation. Employing the methodology developed by Davis and Haltiwanger (1992) for the measurement of job reallocation, we find that at any phase of the business cycle a significant amount of credit flows across U.S. firms. Credit reallocation well exceeds net credit changes and is highly volatile. We also find that, as a result of a procyclical credit creation and a more mildly countercyclical credit destruction, credit reallocation is moderately procyclical. Finally, most of the magnitude and dynamics of credit reallocation reflect credit flows across firms relatively homogeneous for size, industry or location. The results imply that recent macroeconomic models with search frictions and lock-in effects in the credit market can usefully complement established models of the flight to quality and the financial accelerator.

In the second chapter, "The Effect of Comovement Between Firms on their Liquidation Values: Do Firms Attract More Trade Credit when their Sales Are Less Correlated?", I analyze whether and in what ways does the degree of comovement of a firm with other firms in its industry, measured by the correlation of their growth rates of sales, affect the amount of trade credit extended to the firm. I find evidence that more trade credit is extended to firms that exhibit a lower degree of comovement with its industry peers. The

results suggest a significant role of the liquidation value of a firm in determining its financial structure as proposed in Shleifer and Vishny (1992).

The third chapter is titled "How Should We Control For the Clustering in Central Bank Intervention Data?" Central bank intervention data is clustered, with successive days of intervention followed by successive days without intervention. We test motivations for intervention by estimating both the autoregressive conditional hazard model and the autoregressive conditional binomial model for interventions by the Federal Reserve, Bundesbank, and Bank of Japan. Utilizing a variety of measures, we find that the former is outperformed by the latter. We find evidence that both the Federal Reserve and Bundesbank preferred to intervene when the market was calmer. The Bundesbank intervened in response to exchange rates being out-of-line with long-run fundamentals, while the spread between the 6-month Treasury Bill rate contains predictive power for Federal Reserve interventions. We find evidence that Japan intervened in response to changes in the nominal exchange rate, and intervention differed before and after Eisuke Sakakibara became Director General of the International Finance Bureau of the Ministry of Finance in Japan.

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Introduction

This dissertation deals with the relationship between financial markets and the real economy. The first chapter is broad in scope; it is devoted to developing basic understanding of the nature and behavior of credit reallocation. The second chapter complements the first one by focusing on one of the aspects of cross-sectional credit reallocation, namely the comovement of firms within a single sector of the economy, and its relationship to the amount of credit extended to firms within the sector. The third chapter is a stand alone chapter that presents, estimates, and compares two empirical models of central bank intervention in the foreign exchange market.

The goal of the first chapter[1], "Credit Reallocation", is to describe properties of credit reallocation among firms. The need for taking a closer look at the process of credit reallocation comes from the importance of reallocation of resources in general. Due to continuous development of new products and technologies on the one hand, and frequent occurrences of various macroeconomic shocks on the other, economic conditions are constantly changing. This presence of never ending change in the circumstances faced by firms and whole sectors of the economy gives rise to reallocation of resources across firms. Davis and Haltiwanger (1992) developed measures of gross flows and reallocation to be used in their study of the reallocation of labor. Ramey and Shapiro (1998) used the same methodology to address the reallocation of physical capital. Both studies found a significant degree of reallocation of these physical resources. Our aim in this first chapter is to improve upon the common understanding of the process of resource reallocation by studying the reallocation of credit across firms. We find that most of the credit reallocation occurs within groups of homogeneous firms, regardless of whether grouped by size, location, or product characteristics. In other words, even though we find that the idiosyncratic nature of credit reallocation is weaker than in the case of job reallocation as reported by Davis and Haltiwanger (1992), we still find that most of the credit reallocation is driven by the idiosyncratic nature of firm credit flows. Since financial credit, when compared to workers as a resource, exhibits virtually no industry specificity, one would expect that financial capital would migrate freely across industry groups. Why then do we not observe more financial credit being reallocated across groups of homogeneous firms in response to changing economic conditions? The second chapter takes a step toward answering this question.

The second chapter, "The Effect of Comovement Between Firms on their Liquidation Values: Do Firms Attract More Trade Credit when their Sales Are Less Correlated?", much narrower in scope, complements the first one by focusing on one aspect of the intra-sectorial properties of credit reallocation. In this chapter, I identify intra-sectorial comovement between firms, measured by correlation of sales, as one of the potential determinants of the amount of credit received. The motivation comes from Shleifer and Vishny's (1992) theory of liquidation value. Shleifer and Vishny (1992) suggest a link between the comovement of firms within a sector and the collateral value of their assets. The objective of this chapter is to empirically test this link, and look for evidence of a relationship between the intra-sectorial comovement and the ability of firms to obtain credit. Shleifer and Vishny (1992) argue that firm's liquidation value is negatively correlated with the degree of comovement of firms in its industry. In turn, there is ample evidence that liquidation value of the borrower affects the willingness of creditors to provide financing. The evidence on the direction of this effect, however, is mixed. On the one hand, there is evidence, for instance in Benmelech et al. (2005), that higher liquidation values lead to higher amounts of credit extended, due to a higher collateral. On the other hand, agency problem can lead to a higher risk associated with higher liquidation values, which, as suggested for instance in Jensen and Meckling (1976) and evidenced in MacKay (2003), may lead to less credit extended. This second chapter provides empirical support for the positive relationship between liquidation values and the ability of firms to obtain financing. In other words, I find that firms in industry sectors with a lower degree of comovement enjoy access to more credit.

The third chapter[2], "How Should We Control For the Clustering in Central Bank Intervention Data?", estimates and compares two models of central bank intervention in the foreign exchange market. Traditional econometric techniques do not always take into account the nature of central bank intervention data, which exhibits a large measure of clustering, corresponding to periods of no intervention and periods of frequent intervention. One of the two estimated models is the autoregressive conditional hazard (ACH) model developed by Hamilton and Jorda (2002), while the second model is the autoregressive conditional binomial (ACB) model developed by Herrera (2004). These two models take advantage of the special nature of clustered data in a time series setting. We find that while the ACH specification is only a minor improvement on a simple probit model, the ACB specification is substantial improvement and turns out to be the preferred estimation technique for the kind of clustered data used in the analysis.

Notes

[1]This first chapter is co-authored with Ana Maria Herrera and Raoul Minetti.

[2]This third chapter is co-authored with Christopher Douglas.

Chapter 1: Credit Reallocation

1 Introduction

The Schumpeterian view of creative destruction has recently gained momentum (Caballero and Hammour, 2005). According to this view, aggregate and allocative shocks continually alter the distribution of production opportunities, generating an intense inter-firm reallocation of resources. Indeed, there is evidence that an intense reallocation of physical inputs occurs at any phase of the business cycle. This evidence is well established for workers (see, e.g., Davis and Haltiwanger, 1992, and Davis, Haltiwanger and Schuh, 1996) and recent studies (Ramey and Shapiro, 1998; Eisfeldt and Rampini, 2005) document a process of reallocation of physical capital.

In contrast with the attention dedicated to the reallocation of physical inputs, the role of finance for aggregate restructuring is mostly neglected. Yet, just like employment changes and investment disguise large inter-firm flows of workers and physical capital, the aggregate net change of firms' external financing may mask large inter-firm flows of financial resources. In particular, two questions arise naturally: are financial resources subject to an intense process of inter-firm reallocation analogous to that observed for physical inputs? If so, what are the properties of this "financial reallocation"? Macroeconomic models with financial imperfections imply that addressing these issues is essential for understanding aggregate restructuring. Consider first the models that emphasize asymmetric information and agency problems in the "vertical"[1] relationships between firms and creditors (e.g., Bernanke and Gertler, 1989; Bernanke, Gertler and Gilchrist, 2000; Holmstrom and Tirole, 1997). These models imply that creditors can monitor firms and thereby enhance their efficient use of workers and capital. Therefore, they imply that credit reallocation is crucial for the reallocation of workers and capital to the most productive firms. Consider next the models that emphasize "horizontal" heterogeneity across firms and the search frictions that the inter-firm reallocation of financial resources can entail. These models imply that, by hindering the inter-firm reallocation of financial resources, search frictions in the credit market can hinder the reallocation of workers and capital to the most productive firms. Thus, in both perspectives investigating financial reallocation yields crucial insights into the (obstacles to the) reallocation of physical inputs.

The goal of this paper is to take a step towards understanding financial reallocation. We focus on credit (debt from firms' perspective),[2] which constitutes the main form of external finance of U.S. corporations. Rajan and Zingales (1995) calculates that in 1991 the aggregate debt to equity ratio of U.S. corporations equalled 1.13.[3] Furthermore, in many years net equity issues are negative (Myers, 2001): for example, in 1999 U.S. non-farm, non-financial corporations increased their external financing by 139 billion dollars; the net additional borrowing was 283 billion dollars while net equity issues were negative. Debt is not only the main form of external finance of U.S. corporations but, according to the literature on credit imperfections, it also has distinct costs and benefits that sharply differentiate it from equity. For example, unlike equity, debt is a "hard claim" that can prevent firms from wasting cash flow and provide creditors with strong incentives to monitor; at the same time, being a hard claim, debt can also exacerbate firms' incentive to add risk to their projects (for more on these and other distinct properties of debt, see Myers, 2001, and Section 5 in this paper).

To measure credit reallocation we adopt the statistical methodology developed by Davis and Haltiwanger (1992) and Davis, Haltiwanger and Schuh (1996) for the measurement of job flows. Employing firm balance sheet data from U.S. Compustat tapes, we compute inter-firm flows of total credit and long-term and short-term credit separately. We do so both for the aggregate economy (excluding firms classified in the "Finance, Insurance, and Real Estate" group) and for the manufacturing sector alone. We first investigate the magnitude and cross-sectional properties of the flows; then, we explore the time series properties of the flows, namely their volatility and cyclical pattern. We document the following stylized facts:

Fact 1. At any phase of the business cycle inter-firm credit flows are important. These flows well exceed those needed to accommodate net credit changes and are of the same order of magnitude as job and capital flows. Thus, an intense process of credit reallocation is continually at work;

Fact 2. Credit reallocation is somewhat larger in manufacturing than in non-manufacturing industries and it varies substantially across manufacturing industries. Furthermore, reallocation does not vary substantially across census regions while it is negatively correlated with firm size;

Fact 3. Inter-firm credit flows exhibit a large volatility (coefficient of variation), above that of job flows. Moreover, while for total credit the volatilities of credit creation and credit destruction are roughly equal, for long-term credit the volatility of credit destruction exceeds that of credit creation;

Fact 4. Credit reallocation follows a moderately procyclical pattern. This is especially evident for the eighties and for the nineties when credit creation was significantly procyclical while credit destruction was only moderately countercyclical. This finding is corroborated by a VAR analysis, which reveals that negative shocks to output growth depress credit reallocation by exerting a downward pressure on credit creation and a milder upward pressure on credit destruction;

Fact 5. Credit flows within groups of firms roughly homogeneous for size, industry or location are substantially larger than credit flows across these groups. In addition, the volatility and procyclical dynamics of credit reallocation mostly reflects the idiosyncratic behavior of debt changes within these narrowly defined groups rather than mean translations of the aggregate or sectorial distributions of the debt changes.

Drawing on these facts, we inquire into the determinants of credit reallocation and its role in aggregate restructuring. The following questions guide us throughout the analysis: do the stylized facts we document support macroeconomic models with credit imperfections? If so, do they allow to discriminate between the second generation of these models (e.g., Caballero and Hammour, 2005; Den Haan, Ramey, and Watson, 2003; Wasmer and Weil, 2004), which emphasize "horizontal" firm heterogeneity and lock-in effects in credit relationships due to specificity or search frictions, and the first generation of these models (e.g., Bernanke and Gertler, 1989; Bernanke, Gertler and Gilchrist, 2000), which emphasize asymmetric information and agency problems in the "vertical" relationships between firms and creditors? Our conclusion is clear-cut: second generation models can explain at least three of the facts we uncover and thus appear to usefully complement established first generation models. Models with search frictions and lock-in effects in the credit market predict that forming credit relationships is more difficult than breaking them and therefore can account for the larger volatility of long-term credit destruction relative to long-term creation (Fact 3). These models can also rationalize the procyclical behavior of credit reallocation (Fact 4). In Caballero and Hammour (2005), reallocation across production units declines during recessions because, as a result of a hold-up problem within credit matches, the creation of credit matches drops, while cumulatively their destruction rises only moderately. Finally, these models can explain the larger importance of idiosyncratic credit flows relative to credit flows across groups of firms with different characteristics (Fact 5). In Wasmer and Weil (2004) and Den Haan, Ramey, and Watson (2003), for example, credit reallocation is governed by a matching function and credit flows to firms randomly, i.e. independently of firms' intrinsic characteristics (such as size or productivity).

The remainder of this paper is structured as follows. In Section 2, we review the related literature. In Section 3, we describe the methodology used to measure credit flows. Section 4 presents summary statistics for the flows and investigates their cross-sectional properties. In Section 5, we examine the predictions that different classes of macroeconomic models with credit imperfections yield about inter-firm credit reallocation and its role in aggregate restructuring. In Section 6, we turn to the time series properties of the flows. In this section, we also study the dynamic behavior of credit reallocation using a VAR. Section 7 concludes. We relegate details on the data and their sources to Appendix 1.

2 Related Literature

There is limited knowledge of the reallocation of financial resources. Using data from U.S. banks' Call Report Files, Dell'Ariccia and Garibaldi (2005) investigates the *inter-bank* reallocation of loans and finds evidence of a significant heterogeneity in bank-level loan dynamics. This work provides valuable information on the dynamics of liquidity in the financial intermediation sector but limited information on the inter-firm credit reallocation. A bank can contract its loans to a firm and expand its loans to another: this will induce credit reallocation across firms but not across banks. Analogously, a firm can contract its borrowing from a bank and expand its borrowing from another: this will induce credit reallocation across banks but not across firms. In fact, recent studies document that a large number of firms borrow from multiple banks and compensate for the contraction of credit by one bank by increasing their borrowing from another (see, e.g., Petersen and Rajan, 1994, and Detragiaghe, Garella and Guiso, 2000). In conjunction with the fact that many firms can also replace bank loans with non-bank credit, these arguments imply that periods of intense inter-bank loan reallocation can be periods of weak inter-firm credit reallocation and viceversa. Indeed, our results support the idea that the reallocations on the supply side and on the demand side of the credit market are governed by different processes.[4]

The paper also relates to the empirical literature on the "flight to quality" (see, e.g., Bernanke, Gertler, and Gilchrist, 1996), which supports established first generation macroeconomic models with credit imperfections (e.g., Bernanke and Gertler, 1989; Bernanke, Gertler and Gilchrist, 2000). One version of the flight to quality argument is that following negative aggregate shocks financiers contract credit to information opaque borrowers, such as small firms, while they accommodate the increasing credit demand of information transparent borrowers, such as big firms.[5] In turn, this flight to quality works as a financial accelerator of recessionary shocks. The facts we uncover imply that inter-firm credit reallocation is a process with distinct properties that extends beyond the flights to quality during recessions documented by this literature. In particular, we find that credit reallocation is a continuous, major process driven not only by the reshuffling of credit across groups of firms, as possibly implied by the flight to quality argument, but also, and to a larger extent, by the reallocation of credit within relatively homogenous groups of firms (e.g., firms of similar size). Consistent with the predictions of second generation macroeconomics models with credit imperfections (and with the results of the job reallocation literature), we find that idiosyncratic credit flows are larger than credit flows across groups of firms and that they explain a disproportionate share of the time variation of total credit reallocation. Furthermore, credit reallocation accelerates during booms and slows down during recessions. This finding does not contradict the argument that flights to quality occur during recessions but are virtually absent during booms (Bernanke, Gertler, and Gilchrist, 1996): in fact, in our data the procyclical behavior of credit reallocation primarily reflects the procyclical behavior of idiosyncratic credit flows within narrowly defined groups of firms. Yet, this finding fits the predictions of second generation models, confirming that these models can usefully complement previous ones. Finally, as anticipated in the Introduction, this paper relates to the empirical literature on the reallocation of labor and physical capital. For example, the procyclical behavior of credit reallocation brings new arguments to the debate on the cyclical pattern of job and capital reallocation. We elaborate on the relationship with this literature throughout the analysis.

3 Methodology

3.1 Overview of the Data

Our main data source is the Standard and Poor's Full-Coverage Compustat tapes, which provide information on the balance sheets and income statements of all publicly traded U.S. firms.[6] There are advantages and drawbacks in using Compustat. On the minus side, Compustat excludes small firms: the average firm in our sample has sales of 961.26 million dollars. On the plus side, Compustat covers a long period, which allows us to investigate the long-run behavior of credit flows: the original sample comprises annual data from 1950 to 2003 as well as quarterly from 1962Q1 to 2004Q3. Furthermore, the comprehensive scope of Compustat enables us to analyze credit reallocation in both manufacturing and non-manufacturing sectors. This is important because, as shown by the job reallocation literature (see, e.g., Foote, 1998), manufacturing and non-manufacturing sectors can feature different restructuring processes. Because we are interested in firms that demand rather than supply credit, we remove all firms in the industry group "Finance, Insurance, and Real Estate".

For the first years of both samples and for the last years of the quarterly sample the number of observations is disproportionately lower than for other years. Thus, we drop these years and work with annual data from 1956 to 2003 and quarterly from 1971Q1 to 2003Q4. In what follows, we employ annual data to construct descriptive statistics of inter-firm credit flows, thus exploiting the length of the 1956-2003 period. We employ instead quarterly data in the VAR analysis.

3.2 Measurement of Credit Flows

3.2.1 Definitions

The finance literature endorses different notions of debt: perhaps the majority of studies concentrate on long-term debt only (see, e.g., Bradley, Jarrell and Kim, 1984), while others include short-term debt (see, e.g., Ferri and Jones, 1979). Short-term and long-term debt typically serve different purposes. Short-term debt mostly covers the time lag between the financing of current business operations (e.g., payment of inventories or wages) and the accrual of returns. Long-term debt typically finances long-term plans, such as the purchase of equipment or structure. We are primarily interested in debt changes that reflect long-term investment and production plans but we do not want to neglect the possibility that firms use short-term debt to finance these plans. Thus, we adopt a flexible approach, presenting results for total debt and separately for long-term and short-term debt.[7]

Following an established practice in the literature, our notion of short-term debt includes all forms of financial debt, such as loans from financial institutions (e.g., revolving credit lines) and dispersed debt (e.g., commercial bills), but it excludes accounts payable to suppliers. There are strong reasons for this exclusion. First, trade credit is frequently used for purposes unrelated to financing (Rajan and Zingales, 1995). Trade credit is often used for transaction purposes: for example, it is used to reduce the frequency of payments to suppliers and, hence, transaction costs or to ensure recourse in case of inferior product quality. Trade credit is also used like advertising to differentiate products. The transaction purposes of trade credit tie its dynamics to firms' commercial policy rather than to their financing policy. Second, even when used for financing purposes, trade credit and other forms of short-term finance differ along important dimensions and are allegedly poor substitutes. For example, trade credit is extended by firms; its contracts are governed by specific factors; moreover, trade credit is very costly and firms use it only when they cannot obtain cheaper financing (Petersen and Rajan, 1994). Indeed, because of its cost, it is unlikely that firms use trade credit to finance long-term investment and production plans, which we are especially interested in.

In 1956-2003 the average ratio of long-term debt to total assets is 35.77%, while for short-term debt net of accounts payable the average ratio is 17.34%. Both ratios increased during the period: for example, the first rose from an average of 17.74% in 1959-69 to an average of 36% in 1990-99.

3.2.2 Measurement Issues

We have to tackle a number of methodological issues in measuring credit flows. The first stems from the fact that a firm generally engages in different projects. Ideally, we would want to measure the reallocation of credit across projects. However, the firm constitutes our unit of observation and we cannot measure credit flows within firms. Thus, we will tend to underestimate credit reallocation.[8]

The second issue regards firm entry. Some firms that enter the data-set are newly founded while others are existing firms that file with the Securities and Exchange Commission, become incorporated, or result from the divestiture of bigger firms. We do not want to count the debt of existing firms as additions to the aggregate stock of credit. To address this problem, we adopt the criterion put forward by Ramey and Shapiro (1998). Typically, the gross book value of physical capital of a new firm is similar to its net book value. Thus, we drop firms that appear in the data-set for the first time *and* have a ratio between the end-of-period gross capital and the end-of-period net capital above 120% (see the remarks in Appendix 1 for further details).

The third issue regards firm exit. This issue is less thorny than firm entry because Compustat specifies the reason that a firm exits from the data-set. Possible reasons are: merger and acquisition, bankruptcy, liquidation, conversion to a private company, leveraged buyout, or unspecified. We consider exits due to merger or acquisition, bankruptcy or liquidation as credit subtractions, while we do not count exits for other reasons (see Ramey and Shapiro, 1998, for an analogous approach and the remarks in Appendix 1 for further details). There is a strong reason to consider the exit of a merged or acquired firm as a credit subtraction. When two firms merge, the management and workforce of either acquire control over the financial resources of the other. Thus, from the perspective of the financiers of either firm, this is at least partly equivalent to reallocating credit between two firms. Indeed, a large body of literature (e.g., Servaes, 1991) finds that the announcement of mergers significantly affects the stock market valuation of target and acquirer, suggesting that mergers have significant real effects.

The fourth issue regards the use of fiscal or calendar year. In Compustat the data for a whole fiscal year are attributed to the calendar year in which the fiscal year ends if the fiscal year ends after May 31st and to the previous one otherwise. We recalculated credit flows partitioning fiscal year data proportionally into calendar years. The results were virtually identical and therefore we chose to use the original data.

The final issue regards the treatment of inflation. Because we want to capture changes in firms' real exposure to financiers and relate the dynamics of credit flows to that of real variables, we deflate the original annual data using the implicit GDP deflator.

3.2.3 Aggregation

The methodology used to measure credit flows replicates that developed by Davis and Haltiwanger (1992) and Davis, Haltiwanger and Schuh (1996) for the measurement of job flows. We define c_{ft} as the average of the debt of a firm f at time $t-1$ and at time t. For a set of firms, we define C_{st} in an analogous manner. We then define the time t debt growth rate of the firm (g_{ft}) as the first difference of its debt divided by c_{ft}. This measure of the growth rate, which is a monotonic transformation of the canonical one, takes values in the interval [-2,2]; for newborn firms g_{ft} equals 2 while for dying firms g_{ft} equals -2.[9] The empirical distribution of the growth rates of total debt (not shown to save space) has a peak close to zero and two spikes of approximately 5% in correspondence of the entry (+2) and exit (-2) of firms. About 68% of the observations are clustered in the interval [-0.5,0.5], while 81% fall in the interval [-1,+1].

We calculate credit creation (POS) as the weighted sum of the debt growth rates of firms with rising debt or newborn firms. Analogously, we calculate credit destruction (NEG) as the weighted sum of (the absolute values of) the debt growth rates of firms with shrinking debt or dying firms. Both these sums are computed weighting the debt growth rate of a firm f by the ratio c_{ft}/C_{st}. Formally,

$$POS_t = \sum_{\substack{f \in S_t \\ g_{ft} > 0}} g_{ft} \left(\frac{c_{ft}}{C_{st}} \right), \tag{1}$$

$$NEG_t = \sum_{\substack{f \in S_t \\ g_{ft} < 0}} |g_{ft}| \left(\frac{c_{ft}}{C_{st}} \right), \tag{2}$$

where S_t is the set of firms in year t. As in Davis and Haltiwanger (1992), we also define credit reallocation (SUM) as the sum of credit creation and credit destruction, and excess credit reallocation (EXC) as the reallocation in excess of the net credit change (NET) expressed in absolute value. Formally,

$$SUM_t = POS_t + NEG_t, \tag{3}$$

$$NET_t = POS_t - NEG_t, \tag{4}$$

$$EXC_t = SUM_t - |NET_t|. \tag{5}$$

A net increase in credit can be attained through a positive value of credit creation and a zero value of credit destruction; similarly, a net decrease in credit can be attained through a positive value of credit destruction and a zero value of credit creation. Thus, EXC measures credit reallocation in excess of the minimum required to accommodate net credit changes.

4 Summary Statistics and Cross-Sectional Properties

In this section, we present summary statistics for the credit creation, destruction and reallocation rates. First, we assess the magnitude of the credit flows. Then, we investigate their cross-sectional properties.

4.1 Magnitude

In Table 1.1, Panel A, we report the average credit creation, destruction and reallocation for the 1956-2003 period and for the 1959-69, 1970-79, 1980-89, and 1990-99 sub-periods. We also report the average credit change and excess reallocation. Starting with total credit, the average credit creation over the sample period equals 11.3%, while the average credit destruction equals 5.97%. Hence, the average credit change is 5.33% and the average reallocation is 17.27% (see Figure 1.1 for the plot of credit change and credit reallocation). Finally, the average excess reallocation is 11.29%. These figures entail the existence of flows of credit in and out of firms which well exceed net flows: on average more than 11% of credit is reallocated across firms each year. Furthermore, the yearly data (not reported) reveal the simultaneous presence of large positive and negative flows at any phase of the business cycle. For example, in each year since 1980 both credit creation and destruction have exceeded 5.6%; in 1975, when net credit shrank by 5.47%, the creation rate was 4.5%; in 1998, when net credit rose by 11.4%, the destruction rate exceeded 8%.

The reader may wonder to what extent the magnitude of the credit flows is attributable to temporary short-term financing shortages.[10] To address this issue, we report summary statistics for long-term and short-term credit. The average reallocation of long-term credit is 17.34%, which stems from a creation of 11.17% and a destruction of 6.16%. The net average change is 5.01%, while the average excess reallocation is 12.01%. The average creation, destruction and reallocation rates of short-term credit are larger than those of long-term credit: the creation rate is 25.37%, the destruction rate is 18.37%, so that gross reallocation is 43.73%; excess reallocation is 31.54%.

The figures for long-term credit suggest that the intense credit reallocation we uncovered is not only the outcome of temporary short-term financing needs. To verify this hypothesis, and in line with Davis and Haltiwanger (1992), we compute a measure of the persistence of the debt changes underlying the flows as

$$P_t = \max\left\{\frac{debt\ growth\ rate\ between\ t\ and\ t+2}{debt\ growth\ rate\ between\ t\ and\ t+1},\ 0\right\}. \tag{6}$$

The maximum persistence occurs when $P_t = 1$: in this case, all the debt change between t and $t+1$ will last one additional year; the minimum occurs when $P_t = 0$. For total debt the unweighted average value of P across positive and negative growth rates is 0.402. The changes of long-term debt are more persistent that those of short-term debt: the mean value of P is 0.42 for long-term versus 0.32 for short-term debt. This confirms that a sizable portion of the credit flows, especially in long-term credit, reflects persistent firm-level debt changes.

Comparison with Job, Capital and Inter-Bank Loan Flows. How large is inter-firm credit reallocation compared with the reallocation of jobs and physical capital and with the inter-bank loan reallocation? To ease comparisons, in Table 1.2, Panel A, we report average credit flows for the 1973-88 period, together with the average flows of jobs and physical capital documented for the same period by Davis and Haltiwanger (1992) and Ramey and Shapiro (1998), respectively. To be consistent with these studies, we restrict our attention to the manufacturing sector. In Panel B, we report credit flows from 1979Q2 to 1999Q2 together with the inter-bank loan flows obtained for the same period by Dell'Ariccia and Garibaldi (2005). To be consistent with their study, we report average quarterly non-deflated flows. The reader should bear in mind two issues when interpreting these comparisons. First, Davis and Haltiwanger (1992) uses plant-level data and Ramey and Shapiro (1998) has information on the reallocation of capital within firms: therefore, these studies tend to capture more reallocation than ours. Second, Ramey and Shapiro (1998) uses Compustat data like us while Davis and Haltiwanger (1992) uses data from the Census Longitudinal Research Datafile and Dell'Ariccia and Garibaldi (2005) uses data from banks' Call Report Files. Thus, the comparison with Ramey and Shapiro (1998) is particularly tight whereas the comparison with the other two works should be performed with some caution.

During the years 1973-1988, the average credit reallocation in manufacturing is 23.01%, the net credit change is 4.43% and the excess reallocation is 15.87%. By comparison, the average job reallocation is 19.4%, the employment growth rate is -1.1% and the excess job reallocation is 15.4%. For physical capital, the average reallocation is 21.2%, net investment is 1.2% and the excess reallocation is 18.9%. Hence, credit reallocation is of the same order of magnitude as the reallocation of jobs and capital.[11] The figures in Panel B are also insightful, as they reveal that the size of inter-bank loan flows is somewhat smaller than that of inter-firm credit flows. For instance, gross (excess) inter-firm credit reallocation amounts to 8.38% (6.29%) while gross (excess) inter-bank loan reallocation amounts to 4.6% (2.69%).

4.2 Cross-Sectional Properties

The observed credit reallocation may stem from two processes: the reallocation of credit within relatively homogenous groups of firms and the reshuffling of credit across groups of firms with different characteristics (e.g., firms of different size or in different industries). The former process reflects firm-level heterogeneity in debt dynamics; the latter may reflect sectorial shocks or different sectorial responses to aggregate shocks. As we better argue in the remainder of the analysis, first generation macroeconomic models with credit imperfections stress the different effects that aggregate shocks may have on the debt capacity of different groups of firms. Bernanke, Gertler, and Gilchrist (1996), for instance, treats size as a proxy for information transparency[12] and studies the incentive of financiers to reallocate credit from small, information opaque firms to big, information transparent ones during recessions.[13] By contrary, second generation models view the allocation of credit as mostly independent of firms' intrinsic characteristics. In Den Haan, Ramey and Watson (2003) and Wasmer and Weil (2004), the reallocation of credit across firms is governed by a stochastic process summarized by a random matching function. As a result of this random process, credit flows with equal probability, say, to a firm with high and low productivity or to a small and big firm.

In what follows, we try to disentangle the contribution of the within-group and the cross-group credit reallocation. We first partition our sample in industries: focussing on the sub-sample of manufacturing firms, we sub-divide it into two-digit SIC industries. We then partition the aggregate sample using two other classification schemes, size and location. In order to gauge the magnitude of the within-group credit reallocation, we construct the W-index as[14]

$$W_t = 1 - \frac{\sum_{s=1}^{S}(|NET_{st}|)}{\sum_{s=1}^{S} SUM_{st}}, \tag{7}$$

with W_t taking on the value of 1 if in year t excess credit reallocation occurs entirely within groups and 0 if it occurs entirely across groups. The rationale is the following. If in group s there is only credit creation or destruction, then $SUM_s = |NET_s|$. If this occurs for every group, then $W = 0$, signalling the absence of reallocation within groups. Yet, there could still be reallocation across groups. If, instead, $|NET_s| = 0$ for each group and $SUM_s > 0$ for some group, $W = 1$ and all the reallocation will occur within groups. In reviewing the evidence below, it is perhaps useful to bear in mind that for jobs Davis and Haltiwanger (1992) obtains strikingly low values of the W-index, less than 5% for each classification scheme (industry, size, or location). We are going to show that in the case of credit a significant amount of reallocation is generated by heterogeneity in firm-level debt dynamics, although the cross-group reshuffling is not as trivial as in the case of jobs.

Industry. In Table 1.3, we report the average credit creation and destruction in each manufacturing industry and in the manufacturing sector over the sample period. For manufacturing as a whole, the magnitude of credit flows is slightly larger than for the aggregate. The average credit creation is 12.97%, while the average destruction is 7.32%. Thus, the average net credit change is 5.65% and the average reallocation is 20.29%. Turning to the single manufacturing industries, we find substantial variability in the magnitude of the flows. For example, credit creation ranges from 21% in Printing, Publishing, and Allied Industries to 10% in Petroleum, Refining and Related Industries. Leather and Leather Products features the highest credit destruction rate (12.82%), while transportation features the lowest (6.33%). The cross-industry range of variation for the net change is 9.98%-1.43%; for reallocation it is 31.64%-17.08%. The substantial variability of the reallocation rate reflects the high positive correlation (approximately 0.5) between credit creation and destruction across industries. The figures for long-term credit are very close to those for total credit and we do not dwell on them (see Panel B).

The most important piece of information we learn from the table is that significant flows of credit creation and destruction coexist within manufacturing industries. This suggests that an important amount of reallocation may not reflect the reshuffling of credit across industries but within-industry heterogeneity in the dynamics of firms' debt. To verify this hypothesis, we compute the $W-$index, where now the generic group s is a manufacturing industry. The value of W ranges from 0.235 in 1956 to 0.746 in 1994 and its mean is 0.546. Thus, although the reshuffling of credit across industries is important, a significant fraction of reallocation is generated by heterogeneity in firm-level debt dynamics.[15]

Size and Location. We decompose the aggregate sample using two classification schemes: size and location. In Table 1.4, Panels A and B, we partition firms in quartiles according to their sales. The data show that a significant amount of reallocation occurs within all the quartiles, both when we consider total credit (Panel A) and its long-term component (Panel B). In fact, the values of the W-index are 0.632 for total credit and 0.627 for long-term credit. Furthermore, even if we use a finer partition of the sample in deciles, we obtain values of W of 0.608 for total credit and 0.605 for long-term credit.

Interestingly, there appears to be a clear negative relationship between the intensity of credit reallocation and firm size. Consider total credit: the average excess reallocation rate drops from 34.02% for the quartile of smallest firms to 9.6% for the quartile of largest firms. This finding somehow resembles that in Davis and Haltiwanger (1992): for the 1975-86 period, they find that excess job reallocation drops from 28.1% for plants with 1-99 employees to 11.9% for plants with more than 1000 employees. Indeed, the result we obtain here is even more noteworthy because the variation occurs across medium-large firms.

In Table 1.5, we partition firms according to their census region. The average credit reallocation ranges from 20.24% in West North Central to 16.51% in East South Central. Thus, in all the census regions an intense process of reallocation is at work suggesting that the reshuffling of credit across regions can only explain a fraction of the observed reallocation. This impression is confirmed when we compute the W-index, which takes on the value of 0.602 (0.625 for long-term credit). Finally, note that the credit reallocation rate varies across regions less than across industries or sales quartiles. This resembles the findings of Davis and Haltiwanger (1992) for job flows, which indeed appear to have a somewhat lower variance across census regions than across industries or size classes.

5 Theoretical Background

One of the most relevant contributions of the literature on gross input (labor and capital) flows has been to discriminate among different classes of theoretical models of the aggregate restructuring process. For example, the studies on gross job flows have shown that embedding shocks to demand, input costs, or technology in macroeconomic models with search frictions in the labor market allows to explain several properties of the flows (for a discussion see, e.g., Davis and Haltiwanger, 1992). This has revealed that we can learn important insights from search models of the labor market. In this paper, we pursue an analogous objective. The main question that guides us throughout the analysis is whether the facts we document support macroeconomic models with credit imperfections. Moreover, we are interested in understanding whether these facts help to discriminate between the first and the second generation of these models, thus shedding light on the main obstacles to the process of aggregate restructuring. For this purpose, in this section we compare and contrast the predictions of these two classes of models with respect to the properties of credit reallocation (further details are in the remainder of the analysis).

5.1 Preliminary Observations

First and second generation macroeconomic models with credit imperfections differ especially in the frictions that shape credit reallocation rather than in the underlying shocks that drive reallocation. In particular, in both these classes of models credit reallocation can be generated by real shocks that continually redistribute production opportunities across firms and by shocks that redistribute liquid funds. Moreover, particularly in first generation models, credit reallocation can be generated by continuous shocks to firms' net worth. In fact, it is well established in the literature that in the presence of credit imperfections the level of debt of a firm is determined not only by its production opportunities and by the current amount of its internal funds but also by the debt capacity of the firm. In turn, since a firm's net worth influences its incentives to behave and declare its characteristics to financiers truthfully, debt capacity is affected by the net worth of the firm and, hence, by its profitability and asset value. These links constitute a standard feature of models with credit imperfections and are extensively investigated in previous papers (see, e.g., Myers, 2001, and Harris and Raviv, 1991 and 1990, for in-depth analyses). For this reason, and because first and second generation models do not differ sharply in this respect, we do not dwell on the nature of the shocks that underly credit reallocation but, for given shocks, we focus on the frictions that shape the reallocation process.

5.2 Second Generation Models

Second generation models emphasize "horizontal" heterogeneity across firms and lock-in effects in the credit relationships between borrowers and lenders due to search frictions and/or specificity. Wasmer and Weil (2004) studies a model economy where firms face search frictions both in the credit market and in the labor market. A financier (banker) can fund the fixed cost that a firm has to sustain to post a vacancy in the labor market. The meeting technology between creditors and borrowers has a stochastic random nature which is described by a matching function. Caballero and Hammour (2005) develops a model where firms carry out indivisible projects within matches that also involve workers and external financiers. The relationship between a firm and the external financiers of its project features partial specificity: if the financiers relocate capital to another match, they will face costs. This specificity generates a hold-up problem: ex post the firm can threaten to break the match and thereby extract rents. Finally, the hold-up implies that too many productive matches are destroyed because financiers are unwilling to inject funds and offset negative cash flow shocks. Furthermore, too few matches are created because, expecting the hold-up, financiers are reluctant to inject funds. Den Haan, Ramey and Watson (2003) develops a model in which the lock-in of financiers stems from search frictions, as in Wasmer and Weil (2004). In their context, projects are divisible but feature fixed costs, so that entrepreneurs who obtain too little credit have the incentive to shirk. Finally, an entrepreneur who obtains little credit from her financier cannot immediately form a match with an alternative financier because of search frictions in the credit market.

All in all, second generation models deliver a number of distinct predictions that can be contrasted with those of first generation models (discussed below): (i) idiosyncratic (within-group) inter-firm credit flows are large and account for an important share of credit reallocation. In Wasmer and Weil (2004) and Den Haan, Ramey, and Watson (2003) credit reallocation is governed by a matching function and credit flows to firms randomly, i.e. independently of firms' intrinsic characteristics (size, productivity, etc.); (ii) search frictions and lock-in effects in the credit market hinder the creation of new credit relationships, dampening the volatility of the creation rate over the cycle. Therefore, these models imply that credit creation is less volatile than credit destruction; (iii) the credit reallocation rate tends to surge during booms and drop during recessions. In Caballero and Hammour (2005), for example, this happens because the creation of credit relationships falls during recessions, while cumulatively their destruction rises only moderately.

5.3 First Generation Models

First generation macroeconomic models with credit imperfections emphasize asymmetric information and agency problems in the "vertical" relationships between entrepreneurs or managers and external financiers. In macroeconomic models with informational asymmetries, financiers have imperfect information on firms' assets, profitability or investment opportunities and may charge high quality firms an "external finance premium". This group of models build on established corporate finance theories such as the pecking order theory (Myers and Mijluf, 1984).[16] In macroeconomic models with agency issues, debt may induce managers to engage in risky projects (risk-shifting) or under-invest (debt overhang) to reduce the expected debt repayment. This group of models, which comprise Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (2000), build on the corporate finance analysis of Jensen and Meckling (1976).

The key empirical predictions of first generation models differ from those of second generation models: (i) credit reallocation is mostly a cross-group phenomenon. For example, Bernanke and Gertler (1989) predicts that during recessions credit flows from small to large firms. In fact, the flight to quality literature has investigated empirically the occurrence of this cross-group reallocation; (ii) credit creation is highly volatile because it reflects the dynamics of firms' net worth besides that of cash flows. In particular, as discussed by Caballero and Hammour (2005), the high volatility of credit creation is jointly driven by fluctuations in firms' profits and in the value of their collateral assets; (iii) credit reallocation tends to follow a countercyclical pattern. Flights to quality occur during recessions because agency costs increase when firms' net worth drops (Bernanke, Gertler, and Gilchrist, 1996).

6 Time Series Properties

Because of the different predictions of first and second generation models, understanding the dynamics of credit reallocation can help us to discriminate between these two classes of models. We investigate the time series properties of credit flows in three steps: long-run pattern, volatility, and interaction with the business cycle.

6.1 Long-run Overview

Table 1.1 shows that credit reallocation surged significantly in the eighties and then dropped slightly in the nineties. In the sixties and seventies, the total reallocation was close to 14% while in the eighties it exceeded 21%. This pattern is also evident for long-term credit. Second generation models offer an explanation for this pattern. According to Caballero and Hammour (2001), in the eighties and nineties the large amount of liquidity generated by the rise in stock market prices fostered sellers' incentives to sustain transaction and search costs and sell assets. This increased the reallocation of physical capital. In this view, credit reallocation may have been crucial to finance this process of reallocation of physical capital. However, this is not the only possible explanation and first generation models can also rationalize the surge in credit reallocation. Holmstrom and Kaplan (2001) argues that the deregulation and advances in information technology occurred in the United States at the end of the seventies uncovered severe agency problems (of the type studied especially by first generation models): inefficient firms wasted cash flow, while efficient ones were under-scaled. In the eighties and nineties, U.S. corporations underwent a massive restructuring, which entailed stock buybacks and takeovers and was largely financed by debt (especially bank loans and junk bonds). If creditors are indeed a source of discipline and monitoring for firms, credit reallocation may have been critical for firms' restructuring. In fact, credit would have migrated from efficient to inefficient firms that needed to discipline their managers.

6.2 Volatility

Credit creation and destruction exhibit significant volatility (see Table 1.1, Panel B). Excluding 1988, when a dramatic rise in short-term credit occurred and the creation rate was 45%, credit creation ranges from 19.01% in 2000 to 4.45% in 1975; credit destruction ranges from 11.01% in 1984 to 1.34% in 1964. The coefficient of variation (100*standard deviation/mean) of credit creation exceeds 39%, while that of credit destruction exceeds 42%; for gross and excess reallocation, the figures are approximately 30% and 41%.[17] To better grasp the magnitudes at stake, it is useful to compare these figures with those for job flows. Using the data from 1973 to 1986 in Davis and Haltiwanger (1992), we calculated that the coefficient of variation of job creation is 24.71%, that of job destruction is 28.83%, while that of job reallocation is 8.82%. Thus, at least for this period, credit flows are more volatile than job flows.[18]

The literature on job flows generally finds that the volatility of job destruction exceeds that of job creation[19] and explains the sluggishness of job creation with the frictions that firms face in hiring workers, such as search frictions (for a theoretical model, see Mortensen and Pissarides, 1994). Seemingly in contrast to this finding, the coefficient of variation of credit creation and that of credit destruction are roughly equal. Yet, if we focus on long-term credit, the coefficient of variation of the credit creation rate (36%) is significantly lower than that of the destruction rate (46%).[20] The finding for total credit is thus due to the dynamic behavior of short-term credit (see Table 1.1, Panel B). Second generation models can rationalize the higher volatility of long-term credit destruction relative to long-term credit creation. In Caballero and Hammour (2005) the destruction of productive matches and credit relationships fluctuates more than the creation of new ones. This occurs because a hold-up problem within credit relationships discourages the financing of production units ex ante and thereby depresses the creation of relationships. The analyses of Wasmer and Weil (2004) and Den Haan Ramey and Watson (2003) yield an analogous implication: just like search frictions in the labor market hinder job creation, search frictions in the credit market render the formation of credit relationships a sluggish process. The corporate finance literature allows to integrate these implications of second generation models and perhaps explain the asymmetry between long-term and short-term credit. Long-term credit entails a long-term commitment by financiers: this exposes financiers to hold-up because they cannot recall funds at will (Diamond, 2004), possibly reinforcing the effect pointed out by Caballero and Hammour (2005).

Sectorial and Idiosyncratic Effects. We have established that a significant amount of credit reallocation occurs within homogeneous groups of firms. Although within groups the cross-sectional variance of the debt growth rates is large in any year, this variance could be constant over time and most of the time variation of credit flows stem from other sources. For instance, the first generation models of Bernanke and Gertler (1989) and Bernanke, Gertler and Gilchrist (1996) predict that the cross-group credit reshuffling associated with flights to quality is volatile, accelerating during recessions and being virtually absent during booms. To discriminate among classes of models it is then critical to assess how much of the time variation of the flows is accounted for by changes in the cross-sectional variance of the idiosyncratic debt growth rates (idiosyncratic effects) and how much by mean translations of their aggregate or sectorial distributions (sectorial/aggregate effects).

We follow Davis and Haltiwanger (1992) and decompose the debt growth rate of each firm in two parts: the sector growth rate (g^S_{ft}), which bundles together aggregate and sectorial effects, and an idiosyncratic component (g^I_{ft}). Formally,

$$g_{ft} = g^S_{ft} + g^I_{ft}. \tag{8}$$

We then recompute credit flows using only the idiosyncratic component of debt growth and denote them by superscript I. Using simple algebra, the variance of a flow equals the sum of the variance of the idiosyncratic flow, the variance of the sectorial-mean component and twice the covariance between the idiosyncratic flow and the sectorial-mean component.

For instance,

$$varSUM = varSUM^I + var(SUM - SUM^I) + 2cov(SUM - SUM^I, SUM^I). \quad (9)$$

If the time variation of credit reallocation is entirely driven by mean translations of the aggregate or sectorial distributions of debt changes, $varSUM^I/varSUM = 0$; if it is mostly driven by changes in their cross-sectional variance, $varSUM^I/varSUM$ will take a high value. The covariance term captures the share of variance that cannot be attributed directly to either effect and signals whether the sectorial/aggregate effects and the idiosyncratic effects work in the same or in opposite directions.

In Table 1.6, we report the variance decomposition using our three preferred classification schemes: size classes, census regions, and two-digit manufacturing industries. The results indicate that a disproportionate share of the total variance of gross credit flows is attributable to the cross-sectional variance of idiosyncratic growth rates. Consider manufacturing industries: about 83% of the variance of the reallocation rate in manufacturing can be attributed directly to idiosyncratic effects while only about 4% can be attributed to mean/sectorial effects. The results for long-term credit are even more remarkable, with almost 86% of the total variance being accounted for by idiosyncratic effects. We obtain similar figures when, focussing on the aggregate, we decompose the variance using size and location as classification schemes: for quartiles of sales, the share of variance explained directly by idiosyncratic effects is 95%.

6.3 Cyclical Properties

We now investigate the cyclical properties of credit reallocation. In Table 1.7, we report pairwise correlation coefficients of the credit flows with unemployment for the 1956-2003 period and for the 1959-69, 1970-79, 1980-89, and 1990-99 sub-periods. The net change of credit is procyclical: the contemporaneous correlation with the unemployment rate is -0.7411, while the correlation with unemployment lead (lagged) one year is -0.6123 (-0.5616). This may indicate that the contraction in credit supply that occurs during recessions overwhelms the increase in credit demand by firms due to the reduced availability of internal funds. The procyclical pattern of the net credit change stems from a procyclical credit creation and a countercyclical credit destruction (see the table).

Turning to credit reallocation, we find that it is also procyclical. The contemporaneous correlation with unemployment is -0.2157; reallocation is also negatively correlated with unemployment lead or lagged one year. The procyclical pattern of credit reallocation is especially evident in the eighties and in the nineties when the correlation coefficients with unemployment equal -0.6773 and -0.8911, respectively. In these two decades, the lack of action on the destruction margin in response to cyclical fluctuations is particularly remarkable: the credit destruction rate is countercyclical but its correlation coefficient with unemployment equals only 0.1654 in the eighties and 0.3196 in the nineties. To save space, we do not report the corresponding tables for long-term aggregate credit and for total and long-term credit in the manufacturing sector. However, the key findings carry over: in all these cases we find that credit reallocation exhibits a procyclical pattern.[21]

The cyclical behavior of credit reallocation fits the predictions of second generation models (Caballero and Hammour, 2005; Den Haan, Ramey and Watson, 2003). In Caballero and Hammour (2005) reallocation across production units declines during recessions. This occurs because, as a result of the hold-up problem, creation falls, while cumulatively destruction rises only moderately. Indeed, we find that in absolute value the correlation of credit creation with unemployment is somewhat larger than that of credit destruction. The procyclical pattern of credit reallocation is also interesting in light of the debate on the cyclical behavior of input reallocation. Davis and Haltiwanger (1992) and Davis, Haltiwanger, and Schuh (1996) find that job reallocation is countercyclical; Ramey and Shapiro (1998) finds that capital reallocation is also countercyclical. Moreover, on the financial side, Dell'Ariccia and Garibaldi (2005) finds that inter-bank loan reallocation is countercyclical, although this result is not easily comparable to the previous ones because the authors focus on the dynamics of excess reallocation.[22] All these findings suggest that the restructuring process accelerates during recessions. However, recent studies are increasingly challenging this view. For example, Foote (1998) finds a procyclical pattern of job reallocation in U.S. non-manufacturing industries; Eisfeldt and Rampini (2005) uses data on acquisitions and sales of property, plant, and equipment from U.S. Compustat Tapes and documents that capital reallocation is procyclical. Our findings for credit reallocation go in the direction of this recent group of studies.

Sectorial and Idiosyncratic Effects. How do the idiosyncratic effects and the sectorial/aggregate effects contribute to the cyclical pattern of credit reallocation? In Table 1.6, bottom row of Panels A and B, we report the correlation coefficient of the idiosyncratic credit flows with unemployment. Consistently across classification schemes, we find that the idiosyncratic flows are negatively correlated with unemployment. Consider manufacturing industries: the pairwise correlation coefficient between unemployment and idiosyncratic reallocation is -0.1617, which slightly drops to -0.1225 for long-term credit. It thus appears that not only idiosyncratic flows drive most of the time variation in credit reallocation, but they also exhibit a procyclical pattern.

6.4 VAR Analysis

In Section 6.3, we analyzed the cyclical properties of credit reallocation using the unconditional correlation between the credit flows and the unemployment rate. Insofar as these correlations can help to discriminate among different theories, it is important to explore whether the moderately procyclical behavior of credit reallocation is confirmed when we employ alternative measures of correlation. Indeed, Den Haan (2000) argues that not only the magnitude but also the sign of the empirical correlations are sensitive to the method employed for their calculation. Furthermore, by focusing on a single correlation coefficient (the unconditional correlation), one looses information regarding the dynamic comovement between economic activity and credit flows.

In this section, we explore the cyclical properties of credit reallocation using a VAR approach. We proceed in two steps. We first examine the dynamic response of credit creation and destruction to exogenous output shocks using a structural VAR. Our focus on output shocks is motivated by the observation that second generation models with credit imperfections focus on the impact of real shocks on credit creation and destruction whereas they are mostly silent about the impact of nominal (monetary) shocks. Next, we provide further evidence on the comovement between output and credit flows using a statistic proposed by Den Haan (2000) which only requires estimation of a reduced-form VAR and, hence, does not depend on particular identifying assumptions. Note that, while in Section 6.3 we focused on the unconditional correlation with the unemployment rate to ease comparisons with the labor and capital reallocation literature, we now focus on the conditional correlation with output growth. In fact, the use of GDP is the norm in VAR studies.

6.4.1 Response to Output Shocks: Evidence from a Structural VAR

To study the effect of output shocks on credit reallocation we consider a quarterly VAR describing the behavior of y_t, a vector that comprises a macro block and a credit flows block. Following the parsimonious approach of Rudebush and Svensson (1999), the macro block includes the log growth of real GDP ($y_{y,t}$), the log growth of the CPI ($y_{p,t}$), and, as a policy instrument, the federal funds rate ($y_{f,t}$).[23] The credit flows block includes the non-deflated credit creation rate ($y_{c,t}$) and the non-deflated credit destruction rate ($y_{d,t}$) of the sector and maturity of interest. We use seasonally adjusted quarterly data spanning the 1971:Q1-2003:Q4 period.[24]

We assume the data generating process for y_t to be given by the following structural VAR

$$\mathbf{B}_0\mathbf{y}_t = \mathbf{B}(L)\,\mathbf{y}_{t-1} + \mathbf{u}_t \tag{10}$$

where $u_t = \left[u_{y,t}, u_{p,t}, u_{f,t}, u_{c,t}, u_{d,t}\right]'$ is a vector of white noise structural innovations uncorrelated with all the variables dated $t-1$ and earlier, with variance-covariance matrix $E\left[\mathbf{u}_t\mathbf{u}_t'\right] = D$, and $B(L)$ is a matrix lag polynomial of order 4.

Our identification strategy is as follows. Let $y_t = \begin{bmatrix} \mathbf{y}_t^m & \mathbf{y}_t^c \end{bmatrix}'$, where y_t^m is the 3×1 vector of macro variables and y_t^c is the 2×1 vector of credit flows. We rewrite (10) as

$$\begin{bmatrix} \mathbf{B}_0^{mm} & 0 \\ \mathbf{B}_0^{cm} & \mathbf{B}_0^{cc} \end{bmatrix} \mathbf{y}_t = \begin{bmatrix} \mathbf{B}^{mm}(L) & \mathbf{B}^{mc}(L) \\ \mathbf{B}^{cm}(L) & \mathbf{B}^{cc}(L) \end{bmatrix} \mathbf{y}_{t-1} + \mathbf{u}_t \tag{11}$$

where B_0^{mm} is a 3×3 lower triangular matrix with ones along the main diagonal, the elements on the main diagonal of the 2×2 B_0^{cc} matrix equal one, and there are no zero-restrictions on the off-diagonal elements of B_0^{cc}. As it is common in the VAR literature, the ordering of the variables in the macro block assumes that output is Wold-causally prior to the CPI and the federal funds rate and that the CPI is Wold-causally prior to the federal funds rate. This ordering reflects the view that monetary policy -proxied by the federal funds rate equation- responds contemporaneously to innovations in the real part of the economy, as does the price level, whereas real production responds to nominal and financial innovations with a lag. Furthermore, by ordering the credit flows last, we allow credit creation and destruction to respond contemporaneously to output shocks. Note that we do not pursue identification within the credit flows block, thus allowing credit creation and destruction to be contemporaneously correlated.

In Figure 1.2, we portray the estimated impulse responses of credit creation (solid line), destruction (dotted line), and net credit growth (dashed line) to a one unit innovation in the GDP, that is an increase in annual output growth by 1%. The figure depicts the responses for short-term, long-term, and total credit for the aggregate and for manufacturing. Response coefficients that are significant at the 1% and 5% levels are respectively denoted by (♦)

and (o) marks on the response function. Significance levels are based on nonparametric bootstrap intervals obtained following the methodology in Runkle (1987).[25]

In all cases, in the aftermath of the shock, the creation rate of total credit exhibits a statistically significant increase. For the aggregate, the peak response occurs five quarters after the shock and entails a total credit creation rate 1.4% above the baseline value, whereas for manufacturing the peak occurs after five quarters and entails an increase of the total creation rate by roughly 1.9%. For long-term credit, the dynamic response of the creation rate is similar to that for total credit: for example, for the aggregate the peak response is realized five quarters after the shock and amounts to 0.9%. The long-run creation effect is positive: the cumulative response of total credit creation at a 16 quarters-ahead horizon is 6.8% for the aggregate and 13.1% for manufacturing.

The shock generally triggers a drop in credit destruction, but the response is weaker than that of credit creation and seldom statistically significant. For the aggregate, the destruction rate of total credit reaches its bottom after two quarters at about 0.3% below the baseline. Cumulating the first 16 impulse response coefficients reveals that the shock induces a slight fall of 0.5% in total credit destruction. For manufacturing, the maximal decline of total credit occurs after four quarters but is negligible (less that 0.2%) and not statistically significant.

Turning to the response of the net growth of total credit granted to the aggregate economy and to manufacturing, the peak occurs after five quarters at 2.9% and 3.4%, respectively. The longer term (16 quarters-ahead horizon) effect on net credit growth is positive, taking on a value of 13.3% for the aggregate and 21.1% for manufacturing. As for total credit reallocation, the results imply that the positive output shock generates a long-run reallocation of 4.0% for credit to the aggregate economy and 9.2% for credit to manufacturing; once we net out the effect of the shock on inflation, the corresponding real figures are approximately 2.8% and 8.0%. Thus, the shock fosters credit reallocation in an economically significant way.

All in all, the shape of the impulse response functions suggests that in the aftermath of a positive shock to GDP growth credit creation rises while credit destruction does not change or slightly drops. Thus, consistent with what found in Section 6.3 using unconditional correlations, credit reallocation appears to have a moderately procyclical behavior.

To better understand the contribution of output shocks to the mean square error of the k-period ahead forecast error, we also compute the variance decomposition. For conciseness, we only report the contribution of each identified innovation, or block of shocks, to the 8-step and 16-step ahead forecast error variance (see Table 1.8). Regardless of the forecast horizon and the type of credit, output shocks account for a larger percentage of the variance of credit creation than of that of credit destruction. This is especially evident for manufacturing where at an 8-step (16-step) ahead forecast horizon the contribution of output innovations is 25.76% (29.36%) for total credit creation and only 3.63% (7.87%) for total credit destruction.

6.4.2 Short and Long Run: Evidence from a Reduced-form VAR

We now explore the cyclical properties of credit reallocation using a statistic proposed by Den Haan (2000) which requires only estimation of a reduced-form VAR and, hence, does not rely on identifying assumptions. Another advantage of this statistic is that it captures dynamic aspects of the comovement between two variables that are neglected by the unconditional correlation commonly used in the business cycle literature. For instance, if the variables are stationary, the correlation statistic at horizon k converges to the unconditional correlation as k goes to infinity. On the other hand, for small k the statistic reflects the comovement between the variables in the short-run, an aspect that is not captured by the unconditional correlation.[26]

The correlation statistic between variables i and j, $COR^{i,j}(k)$, is computed as follows. Consider the reduced-form VAR

$$\mathbf{y}_t = \mathbf{c}{+}t + \mathbf{A}(L)\,\mathbf{y}_{t-1} + \mathbf{e}_t \tag{12}$$

where $\mathbf{y}_t$ is the vector of endogenous variables described in the previous section, $\mathbf{c}$ is a vector of constants, t is a time trend,[27] $\mathbf{A}(L)$ is a matrix lag polynomial of autoregressive coefficients, and $\mathbf{e}_t$ is a vector of serially uncorrelated but possibly contemporaneously correlated innovations. The k-period ahead forecast of the vector $\mathbf{y}_t$, given the information at time t, is

$$\widehat{\mathbf{y}}_{t+k|t} = E_t\left(\mathbf{c} + (t+k) + \mathbf{A}(L)\,\mathbf{y}_{t+k-1} + \mathbf{e}_{t+k}\right). \tag{13}$$

and the series of k-step ahead forecast errors can be generated as the difference between the realization $\mathbf{y}_{t+k}$ and the forecast $\widehat{\mathbf{y}}_{t+k|t}$. To compute the correlation statistic between output, $y_{y,t}$, and credit creation (destruction), $y_{c,t}$ ($y_{d,t}$), at horizon k we then estimate the 5 variable reduced-form $VAR(4)$ in (12). Next, we compute the forecast at horizons $k = 1, 2, ..., 40$ and generate the series of forecast errors for the level[28] of output, $y^{ue}_{y,t+k}$, and credit creation (destruction) $y^{ue}_{c,t+k}$ ($y^{ue}_{d,t+k}$). Finally, we compute the correlation coefficient between $y^{ue}_{y,t+k}$ and $y^{ue}_{c,t+k}$ ($y^{ue}_{d,t+k}$).

Figure 1.3 plots the computed $COR^{i,j}(k)$ coefficients between output and total credit creation and destruction. The results can be summarized as follows. For total credit to the aggregate economy and to manufacturing, the correlation of output and creation is positive across forecast horizons. The forecast errors for aggregate credit destruction and output are mildly positively correlated both in the short and in the long-run. As for manufacturing, while the forecast errors for credit destruction and output appear to be negatively correlated in the short-run, they are mildly positively correlated in the long-run. All in all, for long forecast horizons, credit creation appears to be procyclical whereas credit destruction is generally acyclical. Although this result is consistent with our finding of a procyclical credit reallocation, driven mainly by the procyclical behavior of credit creation, we should note here that this statistic cannot be computed with a high degree of precision. In fact, we cannot reject the null of a zero correlation at a 5% significance level.[29]

7 Conclusion

In this paper, we have argued that investigating the inter-firm reallocation of credit is important for understanding aggregate restructuring and its obstacles. We have then inquired into the existence of a process of inter-firm credit reallocation. The facts we have documented support recent macroeconomic models with search frictions and lock-in effects in the credit market, implying that these models can complement more established macroeconomic models with credit imperfections. These facts can be wrapped up as follows: i) Inter-firm credit flows are large, at least as large as those of physical inputs. An impressive credit reallocation occurs within homogeneous groups of firms, although the reshuffling of credit across the groups is non-trivial. This reallocation is significant throughout the post-war period and peaks in the 1980-1989 decade; ii) Credit flows exhibit significant volatility, which primarily reflects time variation in the magnitude of idiosyncratic debt changes. For long-term credit, the volatility of credit destruction is larger than that of credit creation; iii) Credit reallocation is moderately procyclical and the results from a VAR analysis reveal that it rises in the aftermath of positive output shocks. In particularly, it appears that the credit creation rate significantly responds to the cycle while the credit destruction rate is more mildly countercyclical. Finally, idiosyncratic flows significantly contribute to the procyclical dynamics of credit reallocation.

We identify two directions for future research. On the theoretical side, the literature on search frictions in the credit market is relatively recent and we still lack a model with precise quantitative predictions on inter-firm credit flows that can be compared with the data. Building such a model is an objective of our current research. On the empirical side, although debt and equity constitute well distinct forms of external finance, we can probably learn important insights from comparing inter-firm credit flows with inter-firm equity flows.

Notes

[1]We borrow the distinction between "vertical" heterogeneity between firms and creditors and "horizontal" heterogeneity across firms from Wasmer and Weil (2004).

[2]Following a vast literature, we consider financial debt and exclude trade debt (see 3.2.1 for more on this).

[3]The ratio is constructed using book values of debt and equity. The aggregate debt/equity ratio is defined as the sum of the debt of all corporations over the sum of their equity.

[4]Clearly, another important difference with Dell'Ariccia and Garibaldi (2005) is that we do not restrict our attention to bank credit.

[5]Firms' liquidity needs tend to rise during recessions because of a shortage of internal funds. A word of caution is due here. The flight to quality argument does not generate strong predictions on the absolute amount of credit extended to different groups of firms. For example, some studies find that during recessions credit extended to small firms declines while others find that it is flat, presumably because of the interaction between a high credit demand and a tight credit supply.

[6]See Appendix 1 for details on Compustat data.

[7]Considering total debt also allows us to control for a measurement issue. In fact, in Compustat long-term debt that will mature in less than one year is included in short-term debt.

[8]Note that a problem of underestimation also arises from the point-in-time nature of the data.

[9]For more details on the properties of the growth rate g_{ft} see Davis and Haltiwanger

(1992).

[10]A similar issue is present in the literature on job flows, where job creation and destruction can reflect short-lived establishment-level employment changes (Davis and Haltiwanger, 1992).

[11]This impression is confirmed when we turn to other sub-periods (values not reported). For example, in manufacturing during the 1970-79 period the average rate of capital reallocation is 16.2%, while the average credit reallocation is 16.35%.

[12]Obviously, size can also reflect technological characteristics of a firm, besides its information transparency. Sometimes the empirical literature on credit imperfections uses proxies of the quality of a firm such as its debt rating. However, this variable is not without limits. For example, the debt rating of a firm is likely to capture especially its current riskiness rather than more broadly its information transparency.

[13]Eisfeldt and Rampini (2007) analyzes the dynamics of liquidity flows in and out of the corporate sector and relates the value of aggregate liquidity to firms' financing shortfalls.

[14]Davis and Haltiwanger (1992) uses a similar methodology.

[15]For short-term credit the mean value of the index is 0.578, while for long-term credit the mean value is 0.57.

[16]In pecking order models (e.g., Myers and Mijluf, 1984), firms use all their cash flow, which is inexpensive because it does not entail informational asymmetries. After exhausting internal funds, they turn to risky debt, which is the cheapest form of external finance; finally, they use more costly finance (e.g., equity).

[17]The coefficient of variation decreases from the quartile of smallest firms (52.07%) to the third quartile (41.75%), while it rises slightly from the third to the fourth quartile

(43.01%). Thus, volatility tends to drop as firm size grows larger.

[18]This is also true if, like Davis and Haltiwanger (1992), we restrict our attention to the manufacturing sector.

[19]Dell'Ariccia and Garibaldi (2005) also finds that the volatility of the flow of bank loan destruction is larger than that of the flow of bank loan creation.

[20]In particular, the variances of the creation and the destruction rate are similar while the average creation rate is larger than the average destruction rate.

[21]Note that, because credit reallocation is defined as the sum of credit creation and credit destruction ($POS + NEG$), the correlation between unemployment (Un) and credit reallocation can be written as

$$corr(SUM, Un) = \frac{sd(POS)}{sd(SUM)} corr(POS, Un) + \frac{sd(NEG)}{sd(SUM)} corr(NEG, Un).$$

In other words, this correlation equals a weighted average of the correlations of unemployment with credit creation and destruction, where the weights are given by the ratios of the standard deviation of creation and destruction relative to the standard deviation of reallocation.

[22]If we restrict our attention to the period considered by Dell'Ariccia and Garibaldi (i.e. 1979-1999), the contemporaneous correlation of the gross reallocation of total debt with unemployment is -0.4894.

[23]The results are robust to using policy instruments alternative to the federal funds rate. In particular, we experimented with the term spread (10 year treasury constant maturity rate - federal funds rate), the quality spread (3-month commercial paper rate - 3-month t-bill),

and the mix (short term debt /(short term debt+commercial paper)).

[24]The credit flows data have been seasonally adjusted with the Census X12 procedure. See the data appendix for a detailed description of the series used in the VAR analysis.

[25]We first estimate the VAR in order to obtain $\widehat{B} = \{\widehat{B_0}, \widehat{B(L)}\}$ and $\widehat{u}_t$. We then take random draws with replacement from $\widehat{u}_t$ and use the bootstraped series $\widehat{u}_t^{(1)}$ together with the parameter estimates $\widehat{B}$, and equation (10) to generate bootstraped data $y_t^{(1)}$. Then, the VAR is fitted to the bootstraped data to obtain $\widehat{B^{(1)}}$, and the impulse response function $\Psi\left(\widehat{B^{(1)}}\right)$. We repeat this procedure 5000 times and then compute 99% (95%) confidence intervals based on the 0.5 (2.5) and the 99.5 (97.5) percentiles of the empirical distribution.

[26]See Den Haan (2000) for more on the properties of the statistic.

[27]A VAR specification without the linear trend produces essentially identical results.

[28]Note that, because the VAR is estimated in growth rates, we accumulate the forecasted changes in the series over the k-period.

[29]The standard errors are computed using the bootstrap method suggested in Den Haan (2000).

Table 1.1: Aggregate Credit Flows

Panel A: Average					
Type of Credit (years)	POS	NEG	NET	SUM	EXC
Total (56-03)	11.30	5.97	5.33	17.27	11.29
Long-Term (56-03)	11.17	6.16	5.01	17.34	12.01
Short-Term (56-03)	25.37	18.37	7.00	43.74	31.54
Total (59-69)	11.26	2.72	8.54	13.98	5.44
Long-Term (59-69)	9.90	2.54	7.37	12.44	5.07
Short-Term (59-69)	32.95	16.69	16.26	49.64	33.38
Total (70-79)	8.00	5.25	2.75	13.25	8.99
Long-Term (70-79)	8.15	5.19	2.96	13.33	10.31
Short-Term (70-79)	20.70	19.11	1.59	39.81	26.49
Total (80-89)	13.03	8.10	4.94	21.13	15.31
Long-Term (80-89)	12.49	8.42	4.07	20.91	15.92
Short-Term (80-89)	27.88	19.68	8.20	47.57	35.60
Total (90-99)	11.59	7.55	4.04	19.15	14.37
Long-Term (90-99)	12.62	8.48	41.34	21.10	16.45
Short-Term (90-99)	25.57	19.75	5.81	45.32	31.77

Panel B: Coefficient of Variation					
Type of Credit (years)	POS	NEG	NET	SUM	EXC
Total (56-03)	39.70	42.48	95.88	30.10	41.25
Long-Term (56-03)	36.38	46.42	79.23	33.45	45.14
Short-Term (56-03)	37.87	32.04	187.59	20.66	21.74

Notes:
The table reports: in panel A, average annual credit flows for the sample period and for the sub-periods; in panel B, the coefficient of variation of the credit flows for the sample period.

Table 1.2: Comparison of Credit, Job, and Capital Flows

Panel A: Manufacturing in 1973-88					
Variable	POS	NEG	NET	SUM	EXC
Total Credit	13.72	9.29	4.43	23.01	15.87
Long Term Credit	13.58	9.70	3.88	23.29	18.11
Short Term Credit	24.34	18.45	5.89	42.79	28.18
Jobs	9.1	10.3	-1.1	19.4	15.4
Physical Capital	11.2	10.0	1.2	21.2	18.9
Panel B: Aggregate in 1979-99					
Variable	POS	NEG	NET	SUM	EXC
Total Credit	5.08	3.30	1.78	8.38	6.29
Long Term Credit	5.59	3.71	1.88	9.29	6.06
Short Term Credit	15.03	12.79	2.23	27.82	22.78
Inter-Bank Loan Flows	3.18	1.42	1.76	4.6	2.69

Notes:

The table reports: in panel A, average annual credit flows, average job flows from Davis and Haltiwanger (1992) and average capital flows from Ramey and Shapiro (1998) in the 1973-88 period; in panel B, average quarterly credit flows and average interbank loan flows from Dell'Ariccia and Garibaldi (2005).

Table 1.3: Credit Flows in Manufacturing Industries

	Panel A: Total					Panel B: Long-Term				
Industry	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
Food	14.79	9.15	5.64	23.93	15.01	14.57	8.66	5.92	23.23	15.63
Tobacco	11.52	7.47	4.05	19.00	5.99	12.05	7.48	4.57	19.54	6.76
Textiles	12.21	10.27	1.94	22.49	11.98	13.25	11.52	1.73	24.77	13.52
Apparel	16.69	10.34	6.34	27.03	14.42	16.96	11.00	5.96	27.96	16.36
Lumber	17.63	7.66	9.98	25.29	10.05	19.20	8.43	10.77	27.63	10.07
Furniture	16.48	11.75	4.73	28.24	14.79	17.13	11.43	5.70	28.56	16.65
Paper	14.05	6.52	7.54	20.57	11.38	14.10	6.92	7.19	21.02	11.87
Printing	20.64	11.00	9.64	31.64	18.52	21.93	12.13	9.79	34.06	20.29
Chemicals	13.10	7.40	5.70	20.51	13.14	13.53	8.06	5.47	21.58	14.23
Petroleum	10.33	6.75	3.58	17.08	8.91	10.55	7.37	3.18	17.92	10.51
Rubber and Plastics	11.51	8.70	2.81	20.21	10.83	12.69	9.82	2.87	22.50	12.56
Leather	16.40	12.82	3.58	29.22	11.71	16.02	12.93	3.09	28.96	11.49
Stone, Clay, and Glass	13.77	8.22	5.55	21.99	11.98	14.58	9.15	5.43	23.73	13.68
Primary Metal	10.67	9.24	1.43	19.90	12.95	11.35	10.16	1.20	21.51	14.57
Fabricated Metal	13.55	10.00	3.55	23.56	13.45	14.46	10.44	4.03	24.90	15.17
Machinery	12.30	6.78	5.52	19.07	10.82	13.29	7.85	5.44	21.14	13.82
Electronic	15.27	9.14	6.13	24.40	14.60	15.51	9.64	5.87	25.15	16.45
Transportation	14.41	6.33	8.08	20.74	9.58	14.28	6.30	7.99	20.58	9.88
Instruments	18.15	9.61	8.54	27.75	15.59	19.20	11.06	8.14	30.25	17.95
Miscellaneous	17.52	13.37	4.15	30.90	17.34	18.60	14.26	4.34	32.86	18.39
Manufacturing	12.97	7.32	5.65	20.29	13.38	13.41	7.91	5.51	21.32	15.22

Notes:
The table reports average annual credit flows for each two-digit manufacturing industry and for the whole manufacturing sector. Panel A refers to total credit; Panel B to long-term credit.

Table 1.4: Credit Flows in Sales Quartiles (Aggregate Data)

	Panel A: Total Credit					Panel B: Long-term Credit				
Quartile	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
0-25%	33.39	21.02	12.36	54.41	34.02	36.29	24.05	12.45	60.34	36.92
25%-50%	24.02	13.15	10.88	37.17	24.54	25.24	14.63	10.61	39.86	27.29
50%-75%	17.16	8.22	8.94	25.38	15.44	17.14	8.70	8.44	25.84	16.74
75%-100%	10.62	5.05	5.57	15.67	9.60	10.46	5.19	5.27	15.65	10.10

Notes:

The table reports: in panel A (B), average annual total (long-term) credit flows over the sample period for quartiles of sales.

Table 1.5: Credit Flows in Census Regions (Aggregate Data)

	Panel A: Total Credit					Panel B: Long-Term Credit				
Region	POS	NEG	NET	SUM	EXC	POS	NEG	NET	SUM	EXC
New England	13.01	6.12	6.89	19.13	9.86	15.19	5.10	10.09	20.29	9.88
Middle Atlantic	10.87	6.77	4.10	17.64	11.21	12.94	5.29	7.64	18.23	9.87
South Atlantic	11.62	5.92	5.70	17.54	10.65	13.49	4.57	8.91	18.06	8.86
E. South Central	11.53	4.99	6.54	16.51	8.16	14.90	4.13	10.77	19.03	7.55
W. South Central	10.79	5.89	4.90	16.68	10.77	12.93	4.55	8.37	17.48	8.94
E. North Central	10.97	5.67	5.30	16.64	9.93	12.51	4.21	8.30	16.72	8.04
W. North Central	13.14	7.10	5.55	20.24	12.37	14.63	4.82	9.81	19.44	9.50
Mountain	13.13	6.20	6.93	19.33	11.57	15.52	5.46	10.07	20.98	10.24
Pacific	11.94	6.75	5.20	18.69	12.36	14.32	5.29	9.02	19.61	10.39

Notes:

The table reports average annual credit flows over the sample period for each census region.

Panel A refers to total credit; Panel B to long-term credit.

Table 1.6: Properties of Idiosyncratic Credit Flows

Panel A: Total Credit

Share of reallocation variance due to	Manufacturing	Size (Quartiles)	Region
i) Sectorial/aggregate effects	0.0398	0.0514	0.0275
ii) Idiosyncratic effects	0.8293	1.2521	1.1281
iii) Covariance term	0.1310	-0.3036	-0.1556
Correlation with Unemployment	-0.1617	-0.1889	-0.1278

Panel B: Long-term Credit

Share of reallocation variance due to	Manufacturing	Size (Quartiles)	Region
i) Sectorial/aggregate effects	0.0248	0.0225	0.0153
ii) Idiosyncratic effects	0.8559	1.1213	1.0854
iii) Covariance term	0.1192	-0.1437	-0.1007
Correlation with Unemployment	-0.1225	-0.1578	-0.0988

Notes:

The table reports the variance decomposition of the flows and the correlation of the idiosyncratic reallocation with unemployment.

Table 1.7: Correlation with Unemployment (Aggregate Data)

	Un.(-2)	Un.(-1)	Un.	Un.(+1)	Un.(+2)
Panel A: Full Sample					
POS	0.0131	-0.3570	-0.5470	-0.4746	-0.3560
NEG	0.3568	0.4906	0.5251	0.3879	0.2689
NET	-0.1689	-0.5616	-0.7411	-0.6123	-0.4485
SUM	0.1832	-0.068	-0.2157	-0.2196	-0.1783
Panel B: 1959-69					
POS	-0.333	-0.7073	-0.7532	-0.6279	-0.3717
NEG	-0.0433	0.5423	0.8197	0.7122	0.8576
NET	-0.2525	-0.7017	-0.7983	-0.6918	-0.5477
SUM	-0.4455	-0.6940	-0.6544	-0.4858	-0.1088
Panel C: 1970-79					
POS	0.3755	-0.3229	-0.8075	-0.2655	-0.1584
NEG	-0.3410	0.1943	0.8996	0.5221	0.2303
NET	0.3848	-0.2729	-0.8833	-0.3942	-0.1944
SUM	0.0419	-0.2349	0.0368	0.3705	0.0172
Panel D: 1980-89					
POS	0.1152	-0.4676	-0.7394	-0.7311	-0.7336
NEG	0.6762	0.8307	0.1654	-0.1853	-0.3555
NET	-0.0349	-0.6318	-0.7651	-0.6913	-0.5472
SUM	0.2607	-0.2755	-0.6773	-0.7271	-0.7717
Panel E: 1990-99					
POS	-0.5484	-0.8218	-0.9370	-0.7910	-0.1544
NEG	-0.2209	0.1158	0.3196	-0.3025	-0.4847
NET	-0.5013	-0.8402	-0.9503	-0.7024	-0.0869
SUM	-0.5823	-0.7871	-0.8911	-0.8499	-0.2162

Notes:

The table reports the correlation of credit flows with unemployment in the sample period (Panel A) and in the four subsamples (Panels B-E).

Table 1.8: Variance Decomposition

	8-step ahead				16-step ahead			
	Output Shocks	Price Shocks	Monetary Shocks	Credit flows Shocks	Output Shocks	Price Shocks	Monetary Shocks	Credit flows Shocks
Panel A: Contribution to aggregate credit creation								
Total	0.097	0.077	0.057	0.769	0.084	0.093	0.056	0.768
Long-term	0.066	0.057	0.051	0.826	0.062	0.106	0.044	0.788
Short-term	0.048	0.033	0.025	0.894	0.051	0.047	0.023	0.878
Panel B: Contribution to manufacturing credit creation								
Total	0.258	0.025	0.086	0.632	0.294	0.032	0.076	0.599
Long-term	0.087	0.092	0.089	0.732	0.079	0.128	0.077	0.716
Short-term	0.221	0.016	0.066	0.697	0.221	0.059	0.060	0.660
Panel C: Contribution to aggregate credit destruction								
Total	0.063	0.060	0.102	0.775	0.065	0.058	0.100	0.778
Long-term	0.007	0.106	0.017	0.869	0.014	0.180	0.033	0.774
Short-term	0.036	0.055	0.034	0.874	0.061	0.094	0.036	0.810
Panel D: Contribution to manufacturing credit destruction								
Total	0.036	0.144	0.049	0.771	0.079	0.146	0.062	0.713
Long-term	0.070	0.089	0.092	0.749	0.068	0.096	0.088	0.749
Short-term	0.041	0.167	0.008	0.884	0.038	0.199	0.025	0.739

Notes:

The table reports the contribution of shocks to 8-step and 16-step ahead forecast error variance.

Figure 1.1: Credit Change, Credit Reallocation, and Unemployment

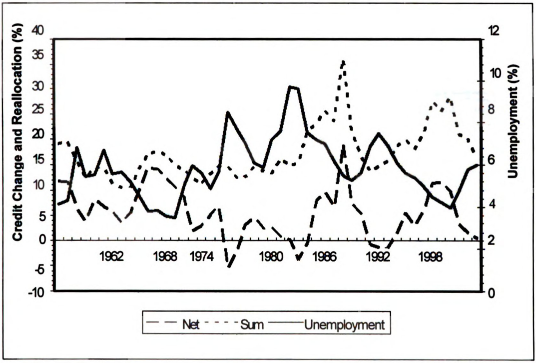
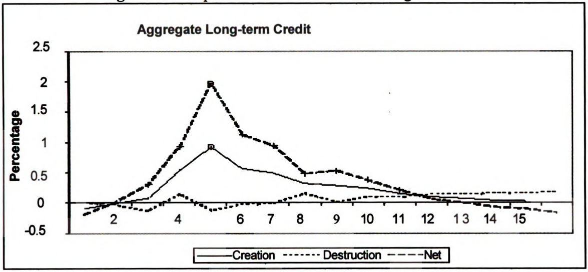
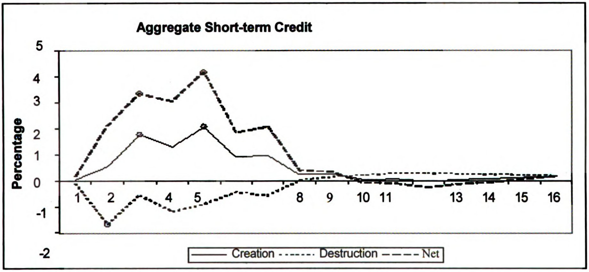


Figure 1.2: Response to a 1% increase in GDP growth



♦ indicates significance at a 1% level   o indicates significance at a 5% level



♦ indicates significance at a 1% level   o indicates significance at a 5% level

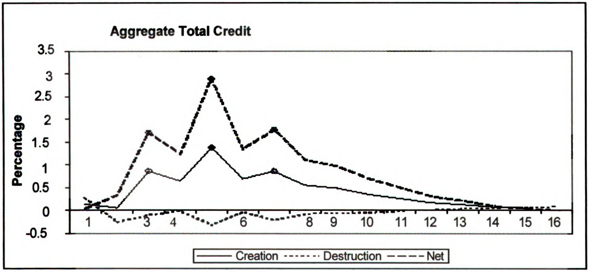
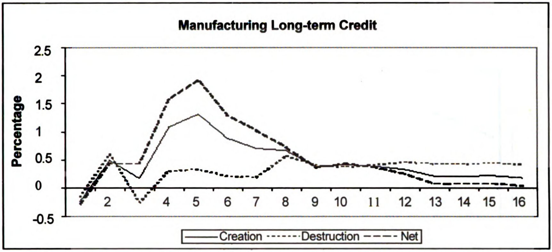
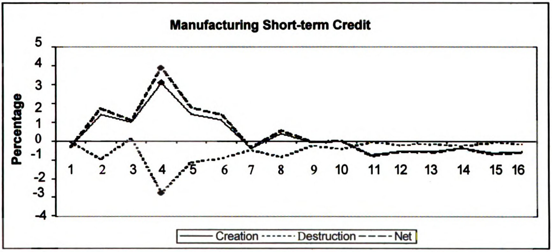


Figure 1.2 (continued)



♦ indicates significance at a 1% level   ○ indicates significance at a 5% level



♦ indicates significance at a 1% level   ○ indicates significance at a 5% level

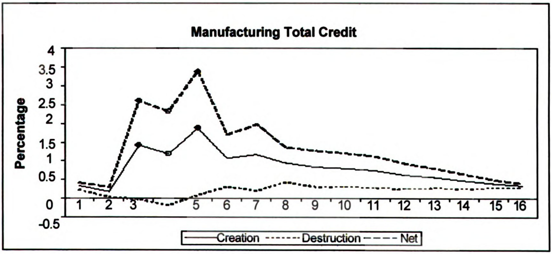
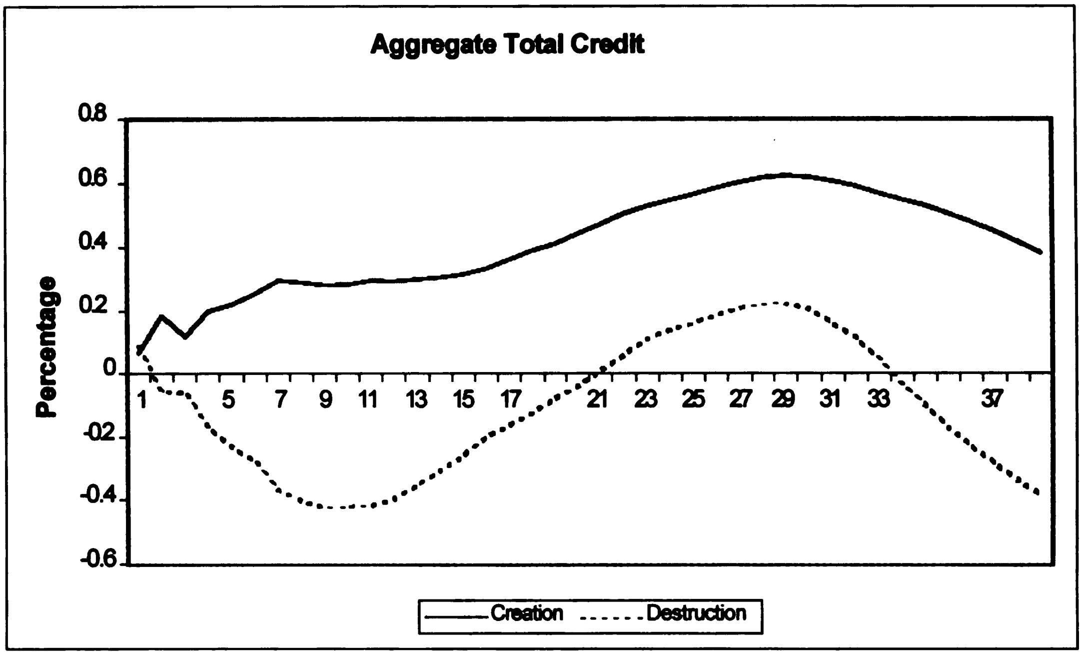
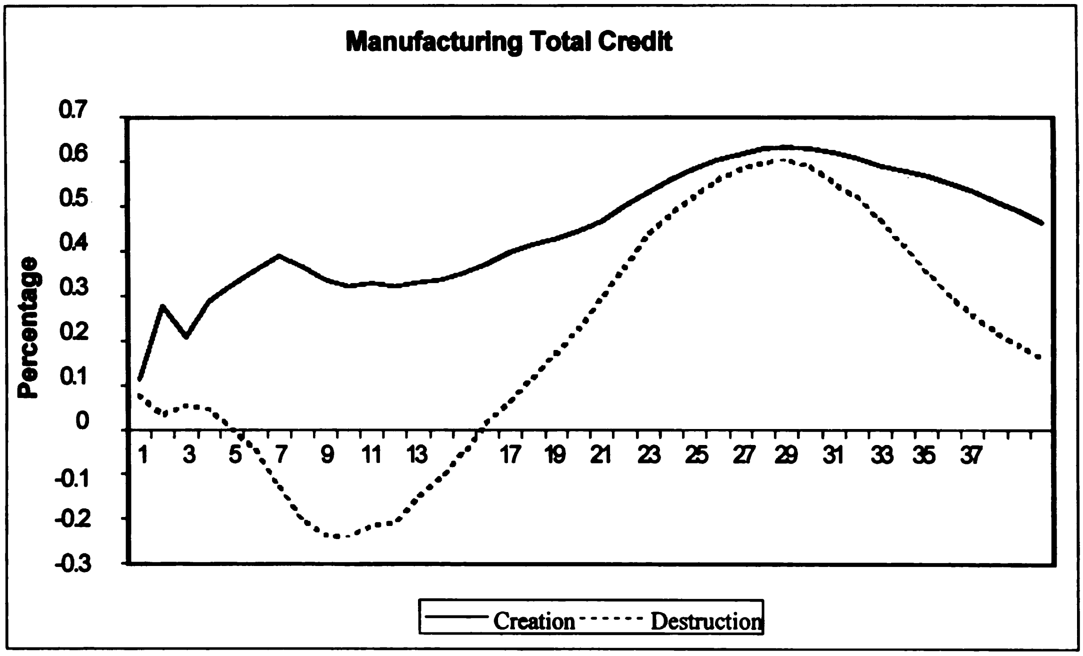


Figure 1.3: Correlation with GDP





Chapter 2: The Effect of Comovement Between Firms on their Liquidation Values: Do Firms Attract More Trade Credit when their Sales Are Less Correlated?

1 Introduction

Why do firms in the same industry get financed differently? Is there an optimal capital structure that firms strive to achieve? Answers to these key questions have eluded researchers for decades.[1] Despite vast research efforts, there is no commonly accepted unifying theory to explain firm capital structure. A recent attempt to reconcile the available theories and empirical evidence was made by Frank and Goyal (2007). As Frank and Goyal (2007) illustrates, the level of disagreement and confusion over the precise role of the determinants of capital structure can be seen in the contradictory implications of two of the most cited studies on the determinants of capital structure, Titman and Wessels (1988) and Harris and Raviv (1991). According to the empirical results obtained by Titman and Wessels (1988), leverage decreases with firm size and leverage is not affected by firm's growth opportunities, the size of tangible assets and non-debt tax shields, while Harris and Raviv (1991) report in their survey of the available empirical evidence the apparent consensus to be that leverage increases with all of these determinants. In other words, despite decades of research since Modigliani and Miller (1958), no consensus has been reached in this area of finance.

Numerous determinants of capital structure have been suggested over time. More recent empirical inquiries include for instance the role of taxes (see for instance Graham (2000)), technology (see for instance MacKay (2003)), stock returns (see for instance Welch (2004)), and testing the static trade-off theories versus the pecking-order theories (see for instance Fama and French (2002)).

In this chapter I focus on a new promising line of research that takes a more detailed look at the impact of industry characteristics on the financial decisions of a single firm. I identify comovement among firms measured by the correlation of sales growth rates as a new determinant of firm finance structure. I provide empirical evidence for this newly identified link. The results suggest a significant, even though somewhat small, impact of comovement on leverage.

Traditionally, the industry effects have been dealt with by simply including industry dummies (See for instance MacKay (2003) for an example). However, recently, two papers have uncovered evidence suggesting a much more complicated relationship between industry and leverage. MacKay and Phillips (2005) find that in addition to overall industry effects the position of a firm *within* its industry also plays an important role in determining its financial structure.[2] Using simultaneous-equation regressions to mitigate endogeneity problems, they find that leverage responds to how close the firm's capital-labor ratio is to the industry median, whether the firm is new, established, or exiting, and to the actions of other firms in the industry. Their evidence is consistent with the competitive industry equilibrium models of Maksimovic and Zechner (1991) and Fries, Miller, and Perraudin (1997). Both of these articles imply that firm decisions are affected by its industry position; Maksimovic and Zechner (1991) express firm industry position in terms of how close its technology is to the industry peers, while Fries, Miller, and Perraudin (1997) use firm status as an entrant, incumbent, or exiting firm as an industry position indicator. In a study related to MacKay and Phillips (2005), Almazan and Molina (2005) investigate the relationship between industry characteristics and the dispersion of leverage ratios among firms in an industry. They find more dispersed leverage ratios in industries with greater liquidity of assets, and in industries with higher proportion of older firms with sufficient growth opportunities.

These two papers were followed by more recent studies. Almazan et al. (2007) confirm that firm's position in an industry matters. They study physical location of firms and find that firms located in industry clusters take on less debt than firms located in rural areas in order to preserve the ability to take advantage of possible acquisition opportunities, which are more abundant within industry clusters. The presence of growth opportunities is the reason for lower debt ratios. In a related study, Loughran (2008) reports the same finding: firms located in rural areas take on more debt than firms located in clusters. However, here the cause for higher leverage in rural areas is information asymmetry. Firms in rural areas face greater information asymmetry problems due to a greater distance from outside investors, which makes it more costly to issue equity, leading them instead to take on more debt.

This chapter introduces a new way of looking at the industry position of a firm. Rather than considering physical location as a measure of the relationship with the industry peers, this chapter investigates the role of comovement among firms, measured by correlation of sales growth rates, in the way firms get financed. The channel through which comovement affects firm financing is via its liquidation value. The link between industry characteristics and liquidation values was first modeled in the context of an overall industry equilibrium by Shleifer and Vishny (1992).[3] Shleifer and Vishny (1992) put forth a theoretical model where the sale value of firm assets depends on how similar its finances are to other firms in the industry at the moment of liquidation. If, for instance, all firms in the industry respond in a similar way to outside shocks, then it is likely that when a firm is liquidated its assets will be acquired by an outside investor due to the lack of available cash on the part of its industry peers that are likely to be in financial distress at the same time. Since outside investors lack the same information and ability to utilize the assets as compared to the industry competitors, the liquidated assets are sold for a fraction of the value in the second best use. Recognizing this *ex ante*, potential creditors will be more reluctant to extend credit due to a lower collateral value to firms in industries with a higher degree of comovement in terms of the likelihood of being financially distressed at the same time. This link has been gaining momentum in the finance literature. For instance Hege and Hennessy (2007) present a model in which incumbent firms deter potential entrants by taking actions that diminish the sale or liquidation value of entrants' assets in the case of entry. Similarly as in Shleifer and Vishny, the liquidation value of assets depends on whether they are acquired by an industry peer or someone outside the industry. In Hege and Hennessy (2007), incumbents issue additional debt creating debt overhang, which prevents them from acquiring new assets. As a result, the collateral value of potential entrants' assets falls, which makes it more difficult to finance the entry, and thus may be enough to prevent entry of new competitors.

This chapter provides empirical evidence consistent with the model of Shleifer and Vishny (1992). The baseline estimate suggests that an increase in the comovement among firms in the industry corresponding to a change from the 25th to the 75th percentile in the sample will lead to a decrease in the accounts payable to assets ratio by around 1.5%, even after controlling for the inventory stock.[4]

Other empirical studies have found mixed evidence concerning the role of liquidation values in corporate finance. For example Benmelech et al. (2005) exploits commercial zoning regulations to find that commercial loans associated with assets of higher liquidation value tend to be larger and come with a lower interest rate. Pulvino (1998) applies the model of Shleifer and Vishny (1992) to the commercial airline industry and provides evidence that the prices that financially distressed airlines receive for their assets are below their fundamental values, which he attributes to a temporary illiquidity caused by the inability of other airlines to raise enough funds to buy these assets at the time.[5] On the other hand MacKay (2003) finds that, depending on whether a firm can commit not to substitute assets, higher liquidity of assets could affect the firm's debt capacity in both directions. He finds on the one hand that, in production, higher redeployability of assets leads to a lower debt capacity due to the inability to commit not to substitute these assets for riskier ones. On the other hand, in the case of assets associated with investment opportunities, since it is possible for the firm to commit, greater flexibility leads to greater willingness of the lenders to extend credit.

My work in this chapter is motivated by the treatment in Shleifer and Vishny (1992). The main idea is when firms' performances within an industry move in unison, it is likely that when one firm goes bankrupt, its industry peers also experience financial difficulties at the same time. Therefore, when comovement is high, for instance because firms in the industry are regularly exposed to common shocks, assets of a fallen firm will be acquired by an industry outsider, who will pay less than the value in the second best use. This may happen, as explained in Shleifer and Vishny (1992), because the firm's industry peers which would normally be in the best position to use the assets will find themselves in financial distress and will be unable to borrow due to agency cost.[6] The industry outsider, due to the lack of expertise and information, will then underpay the value of the assets in its second best use. Thus, when comovement of firms within a sector is high, using the results of Shleifer and Vishny (1992), the liquidation value of an average firm will be low and vice-versa. Comovement, then, will affect the sale value of firms' assets, thus affecting their collateral value and debt capacity. I hypothesize that higher comovement lowers the collateral value thus leading to a lower payment to the lenders in the case of default and their decreased willingness to extend credit. The results provided in this chapter support this hypothesis.

In this chapter I focus on the part of corporate debt that originates from other firms, namely trade credit. Trade credit is a good starting point in this line of research because the amount extended to a firm is likely to depend more heavily on the firm's liquidation value relative to other forms of credit. It is natural for the suppliers of trade credit to factor in their ability to repossess and resell the assets before they provide them to the recipient.[7] For example Boeing will consider its ability to resell an aircraft before it is provided to an airline via trade credit. If airlines comove together, Boeing will recognize that its ability to resell the aircraft at its fundamental value is severely limited because other airlines are likely to experience financial difficulties at the same time. Indeed, Pulvino (1998) does find that airlines in financial distress do sell their assets at a significant discount. Is one of the reasons for this kind of discount a higher comovement of airlines causing the demand for these assets by other airlines to drop precisely when an airline is likely to attempt to sell them?

In addition to the sale of assets being more natural for the suppliers of trade credit than for banks, there is another reason why it makes sense to focus on trade credit. Whereas in both the case of bank loans and the case of corporate bonds the issuers frequently account for the difference in the default risk by adjusting the rate of interest associated with the loan, the issuers of trade credit commonly keep the price terms the same for all firms within the same industry, while instead adjusting the amount of trade credit.[8] Therefore, with trade credit I can simply focus on the amount of credit extended without having to track the terms also. Indeed, I find evidence that the amount of trade credit does depend on the degree of comovement between firms, even after controlling for the stock of inventories which is commonly used as a proxy for the collateral value.[9] I leave it to further research to extend this analysis beyond the area of trade credit.

The rest of this chapter is organized in the following way. Section 2 describes the determinants of trade credit and the data. Section 3 presents the empirical model. Section 4 describes the results, and section 5 concludes.

2 Measurement

First, I discuss measuring the amount of trade credit extended to a single firm. I then proceed to discuss the explanatory variables, starting with comovement, the credit determinant of the main interest. To this key variable I add the determinants of trade credit studied by Petersen and Rajan (1997), who provided an extensive overview of the evidence on trade credit, while adding evidence of their own. To this set of controls, I further add inventories and market interest rate, which were recently also found to significantly influence trade credit (See for instance Choi and Kim (2005)). Inventories are of special interest here because higher inventories make it easier to liquidate a firm's assets and therefore increase the firm's liquidation value. Thus, since I control for the effect of inventories in my regressions, the coefficient on comovement should indicate its true effect on the collateral value, instead of picking up the effect of inventories.

2.1 Measuring Trade Credit

There are two balance sheet trade credit items. Accounts receivable measures the amount of trade credit extended *by* the corresponding firm, while accounts payable measures the amount of trade credit extended *to* the firm. In this paper, I investigate the relationship between the level of comovement of firms in an industry and the amount of trade credit extended *to* a single firm. Accounts payable is therefore the proper dependent variable to be used in the empirical model that estimates the role of comovement in firm financing.

2.2 Comovement Measure

I define comovement at an industry level as in Guiso and Minetti (2004), which is, in spirit, very similar to an alternative definition of comovement at a firm level found in Comin and Mulani (2006).[10] Both measures are based on the growth rate of sales, however the industry level of comovement is more appropriate in my analysis, because it is more consistent with the reasoning behind the model of Shleifer and Vishny (1992). The asset illiquidity effect delivered by the model of Shleifer and Vishny (1992) rests on the assumption that firms in the industry in question are hit by common shocks.[11] In fact, the effect completely disappears if the shock that causes firm liquidation is idiosyncratic. Indeed, as Shleifer and Vishny state in the abstract, they use the model "to explain variation in debt capacity across industries and over the business cycle,...", and use the airline industry as an example of an industry where asset liquidation values are well below their fundamental values because airlines are affected in a similar way by the business cycle. In other words, I expect the debt capacity of firms to be higher in industries where the asset illiquidity effect is present, because firms in these industries comove together. This is the link between industry and asset liquidity that I investigate in this chapter.

My comovement variable therefore measures the degree of comovement of all firms within an industry sector. As stated in the introduction, I hypothesize that firms with a higher industry level comovement value, ceteris paribus, should attract a lower supply of trade credit than firms in other industries with lower levels of industry comovement.

Following Guiso and Minetti (2004) I define the sectorial comovement as the degree to which firms' sales comove together within a single industry. I measure this comovement in the same way as in Guiso and Minetti (2004), by computing R-squared from a regression of real sales growth rate on time dummy variables, using time periods from $t = -4$ to $t = +5$. Using time period windows in constructing the comovement variable allows for the measure to vary over time.

$Comovement_{I,t} = R - Squared$ from the following regression

$$g_{i,t} = \alpha + D_t\delta + u_{i,t}, \text{ for each } i \text{ in } I \tag{1}$$

where $g_{i,t}$ is the growth rate of real sales, α is the intercept, D_t is a vector of time dummy variables, $u_{i,t}$ is the error term, I indexes an industry sector, i firm, t time period, and where $t = \{-4, \ldots, +5\}$.

The reasoning behind this measure is that if firms within an industry exhibit a higher level of comovement, then time dummy variables should explain most of the variation in the growth rate of real sales. In the extreme, if all firms in an industry grow their sales by the same percentage, then R-squared will equal one. In the extreme opposite scenario, if firms' sales in an industry are uncorrelated, then R-squared will equal zero.

2.3 Main Independent Variables

Following Petersen and Rajan (1997) I include measures of firm size, profitability, access to internal funds, rate of growth, firm age, and current assets. A full description of the measures used in the estimation is found in table 2.1.

Because of the data limitations stemming from working with Compustat data, I am unable to control for the relationship between firms and financial institutions. Petersen and Rajan (1997) do not find any evidence that relationship with financial institutions affects the amount of trade credit supplied to the firm, however they do find some evidence suggesting that firms with closer ties to lenders demand less trade credit.

Due to data limitations, I am also unable to include the price of trade credit. This absence should not affect the results in any significant way for two reasons. First, as stated previously, credit terms within an industry are rarely changed. Instead, trade credit may be reduced or withheld entirely from firms with a higher risk of default (See Petersen and

Rajan (1997) and Smith (1987)). Second, the inclusion of industry dummies should account for the differences in pricing among industry sectors.[12]

Another potential disadvantage stemming from working with Compustat data is absence of smaller firms, because Compustat consists of data collected exclusively from publicly traded firms. There is, however, some evidence suggesting that smaller firms behave in a way similar to large firms in regard to obtaining trade credit. For instance Nilsen (2002) evidenced that both small and large firms use more accounts payable during recessions, even though the increase is somewhat larger for large firms. Further, Nilsen (2002) argues that the size of a firm is not decisive for credit quality of a firm as a borrower, and shows that even among large firms the firms with a lower credit rating use much more trade credit during recessions, while large firms with a higher credit rating use other forms of credit, which suggests that credit constraints play important role even among large firms. Thus, it appears that limiting data to a pool of larger firms may still yield a mix of firms with the borrowing behavior characteristics representative of the population of firms in the overall economy.

The last potentially problematic omission I am aware of is the omission of the percent of inventory in terms of finished goods. Again, this is due to data limitations. I do however control for the total inventory stock, which should mitigate this problem somewhat.

Firm Size and Age. Firm size is typically used as a control variable in models where accounts receivable is the dependent variable. While the financial assistance view suggests that larger firms extend more trade credit, the quality verification theory (see Long, Malitz and Ravid (1993)) instead implies that it is smaller firms which extend more trade credit. I am unable to offer evidence on this point since I view the firms in my data set as the users of trade credit rather than suppliers.

The effect of firm size and age on accounts payable is also unclear. On the one hand, it is commonly thought that investment opportunities are negatively correlated with both size and age, which means that demand for trade credit should decline with size and age as investment opportunities shrink. On the other hand, larger and older firms are usually associated with lower risk of default (see for instance Diamond (1989)), implying that the supply of trade credit to these firms may be higher. I use the book value of assets to measure firm size, which is a standard approach, used for instance by MacKay (2003). I approximate firm age by the number of quarters it has been present in the Compustat database.[13]

Profitability. It is commonly believed that profitable firms have more investment opportunities, and therefore need more financing. However, high profitability also attracts lenders, and therefore a highly profitable firm should have no difficulty in obtaining credit elsewhere, and according to the pecking order theory (see for example Graham and Harvey (2001)) should thus demand less trade credit.

Availability of Internal Funds. Greater availability of internal funds raises the creditworthiness of the firm and may increase the amount of trade credit extended to the firm. On the other hand, according to the pecking order theory, demand for trade credit by the firm will decrease with growing sources of internal funding. I follow Petersen and Rajan (1997) in using net income not only as a measure of profitability, but also as a proxy for internal funding availability rather than the more standard measure of cash flow which adds depreciation to net income.[14] For added robustness, I also use another measure of internal sources of funding, retained earnings, which measures the cumulative earnings that have not been paid out as dividends.

Rate of Growth. Growing firms tend to have more investment opportunities and therefore should demand more trade credit. Following Petersen and Rajan (1997) I use change in sales standardized by assets to proxy for how fast the firm is growing.

Current Assets. I can partially control for the demand for short term credit by including a measure of current assets in the model. As established in earlier studies (see for instance Diamond (1991)), firms finance current assets almost exclusively with short term credit. Thus a higher share of current assets in relation to the total assets should result in a higher demand for trade credit.

2.4 Other Controls

Inventory Stock. On the one hand, inventory stock can be positively correlated with accounts payable due to a higher liquidation value. Since it is generally easier to sell inventories than other assets, the firm's liquidation value will be higher with higher inventories and therefore the firm as a recipient of trade credit may be able to attract more credit as it may be perceived to have a higher collateral value and thus represent a lower risk to the lender.[15]

On the other hand, as mentioned in the introduction, assets with higher liquidation values are more liquid and therefore make it easier for the recipient to substitute other, more riskier assets.[16] Therefore, a higher collateral value could represent a greater, not lower, risk to the lender.

Market Interest Rate. The transaction cost theory suggests that both the demand for (accounts payable) and the supply of (accounts receivable) trade credit should increase when the market interest rate rises. Ferris (1981) shows in his model that trade credit reduces the uncertainty of money flows in case of uncertain delivery dates. If delivery dates are uncertain, trade credit has an advantage over bank loans in that it will reduce this uncertainty jointly, not separately, for the recipient and the supplier of trade credit. In Ferris (1981), trade credit is optimal if it is not more than twice as expensive as credit from a bank. Since a higher market interest rate makes bank credit more expensive, more firms will find it optimal to use trade credit instead when the market interest rate rises.

Alternatively, Norrbin and Reffett (1995) also provide a rationale for a positive relationship between accounts payable and nominal market interest rate. Their cash-in-advance model suggests that an increase in the nominal interest rate leads to an increase in the ratio of real trade credit to real balances. They also support this result with empirical evidence.

2.5 Data

I employ quarterly data retrieved from the Compustat database.[17] The upside of using Compustat is the large number of firms covered. The downside of using Compustat is the fact that smaller firms do not typically enter the database.[18]

Quarterly data ranging from 1975:1 to 2005:4 are available from Compustat for the firm balance sheet variables outlined previously.[19] The database allows me to distinguish among industry sectors at the 4-digit SIC level. As is common in the studies of corporate finance (see for instance Fama and French (2002), Molina and Preve (2005), or Opler and Titman (1994)) all observations corresponding to the banking, insurance, and real estate industries (SIC 6000 to SIC 6999) are removed because the operations of these firms include the provision of financial services, and are therefore inappropriate for a study of corporate finance.[20] Also, following Petersen and Rajan (1997), services industries (SIC 7000 to 8999) are eliminated as well. Also in accordance with the other studies[21], observations with zero or missing accounts payable, sales or assets are deleted as well.[22] There remain 374,379 firm-quarter observations that are used in the main analysis, spanning 1976:2 to 2004:3.[23] On average there are around 3284 firm observations in each year quarter, and within each year quarter around 10 firm observations per each of the 340 4-digit SIC industry sectors.

Table 2.1 contains description of all of the variables used in the estimation of the empirical model that is outlined in the next section.

3 The Empirical Model

Following Petersen and Rajan (1997), I normalize accounts payable, the dependent variable, by total assets.[24] Assets are used to scale accounts payable because the ratio of liabilities to assets represents a common measure of leverage. Since accounts payable is a liability, the ratio of accounts payable to assets can be thought of as corresponding to firms' balance sheet management in terms of the relationship between assets and liabilities. It then makes sense to use assets also for scaling the dependent variables.

Then, the empirical model of interest for firm i at time t is:

$$\frac{AP_{i,t}}{Assets_{i,t}} = X_{i,t}\beta_1 + .. + X_{i,t-4}\beta_4 + \gamma_1 Comove_{i,t} + .. + \gamma_4 Comove_{i,t-4} + D_t\delta + D_I\omega + a_i + u_{i,t}, \tag{2}$$

where $AP_{i,t}$ is accounts payable of firm i at time t (Compustat data item 46), $Assets_{i,t}$ is total assets (item 44), $Comove_{i,t}$ is as defined in the previous section, D_t is a vector of time (year and quarter) dummy variables, D_I is a vector of industry dummy variables at the 4-digit SIC level, and $X_{i,t}$ is a vector of other explanatory variables described in the previous section. Four lags of independent variables are included as is customary in regressions with quarterly data.[25] The error term $u_{i,t}$ is complemented by a time invariant variable unique to each firm, denoted a_i. This specification allows for two estimation techniques, depending on the assumptions made about a_i. At first, I use the pooled OLS estimator under the assumption that a_i is uncorrelated with the other explanatory variables and therefore can be safely left as a part of the error term. Since the correctness of the assumption underlying the pooled OLS estimation can be easily questioned, I also estimate the model by the fixed effects estimator, allowing for arbitrary correlation between a_i and the regressors.

3.1 Tariff as Instrumental Variable

Next, I relax the exogeneity assumption on Comovement by introducing an instrument, the degree of protection from foreign competition. I measure the degree of protection by average tariff rates available by 4-digit SIC categories.[26] Firms in industries that are protected by tariffs from foreign competition will be shielded to a certain extent from competitive pressures. Thus, firms in such industries will be less likely, in any given period, than otherwise similar firms that are unprotected, to encounter losses or exhibit a decline in sales. In other words, firms in industries protected by tariffs should exhibit more steady performances in terms of profits and sales. As a result, there should also be less disparity in performance among firms in a protected industry, with the disparity in performance declining with increasing tariff rate. Thus, I expect a positive correlation between tariff rates and comovement.

Any instrument must fulfill two conditions. First, it must be correlated with the endogenous variable that it is instrumenting, which I confirmed by regressing the comovement variable on all exogenous regressors in the model, including the instrument, finding the coefficient on tariff positive and significant.[27] Second, the tariff rates must be uncorrelated with the error term. One cannot test the exogeneity of the instrument, however, since tariff is a policy variable, it is reasonable to assume that it is uncorrelated with the industry-endogenous elements left in the error term. For this reason, tariff rates as an instrument are more appealing than other measures of the degree of industry concentration, such as the Herfindahl index, which clearly violates the instrument exogeneity assumption.

As described in the next section, the magnitude and the direction of the estimated effect of comovement on the supply of trade credit is preserved when using the tariff rates as an instrument. However, the significance is lost. I conjecture that this is due to a loss in precision of the estimate caused on the one hand by less than perfect correlation between the instrument and the instrumented variable, and on the other by the loss of more than half of the observations when using the tariff data. Alternatively, the change in significance could be caused by misspecification of the earlier models, if the comovement variable is endogenous. If this is the case then the true effect of comovement is much less significant than suggested by the results from the non-instrumented regressions.

4 Results

4.1 Summary Statistics

Summary statistics for the main variables are provided in Table 2.2 for the full sample, and also for ten year time periods. The median value of accounts payable standardized by total assets, the dependent variable, is 0.083. It seems to be fairly stable over time. The independent variable of most interest in this paper, comovement, is almost twice as high on average in the 1976-1985 period, the first 10 years of the sample, than in the last two ten year periods. A similar pattern can be observed for the book value of assets, the variable indicating the size of firms. Even though the average size stays about the same, the median firm size appears to be about twice as large in the 1976-1985 period than in the 1985-1995 period. One may be tempted to think that the greater proportion of smaller firms caused the median comovement to come down during 1985-1995, however the results in section 4.2 suggest otherwise. The median profits divided by total assets decline from 0.014 in the first decade to 0.009 and 0.007 in the last two decades of the sample, with the average profits turning negative during these two decades. Change in real sales and current assets less cash seem to be pretty stable in proportion to assets over time. The summary statistics on age are not of much interest, because of the nature of approximating this variable. Naturally, the average length of time since entering Compustat is growing with time.

Summary statistics for comovement are shown separately for each 2-digit SIC industry group in Table 2.3. The median value is the lowest in sector 13, oil and gas extraction, only 0.004. The highest median value, 0.608, is found in group 53, general merchandise stores. If we narrow our attention to manufacturing, the median comovement value ranges from 0.023 in electronic equipment (group 36) to 0.305 in stone and glass (group 32). If we assume that the firms in the two industries are otherwise similar, then, according to the hypothesized effect of comovement on the supply of credit, we should observe a higher accounts payable to assets ratio in the electronics industry, because of higher average liquidation values, than in stone and glass. Indeed, looking at the sample summary statistics, we find that the median accounts payable to assets ratio is higher for electronics (0.085) than for stone and glass (0.078), even though the difference does not appear to be very large.

4.2 Results

4.2.1 Pooled OLS and Fixed Effects

Table 2.4 shows the results for the non-instrumented pooled OLS and fixed effects.[28] The first row provides evidence that a firm located in an industry sector with a higher degree of comovement can expect to see a lower amount of credit supplied to it from other firms. Let us look at the results in more detail.

First, observe that the results are very similar across the two columns. Therefore, I will only describe in detail the results obtained by using the preferred fixed effects model. This method is superior to pooled OLS because, as mentioned before, it corrects for the presence of an idiosyncratic unobserved firm effect, which is very likely to be present in the panel data obtained from Compustat. Moreover, the fixed effects estimation technique is widespread in finance studies, thus my results from the fixed effects estimation are more comparable to other studies in this area.[29]

Consider then the results in the fixed effects column of Table 2.4. It is estimated that an increase in the comovement variable by one will lower the ratio of accounts payable to assets roughly by 10.3%. Put in a more meaningful way, a ceteris paribus increase in the comovement among firms in an industry sector from the 25th to the 75th sample percentile (0.023 to 0.163) will lower the accounts payable to assets ratio for all firms in the sector by around 1.5%. This means for instance that the median sample firm, taken by the accounts payable to assets ratio, would experience a decline in the ratio from around 0.083 to 0.08175. This effect, despite being somewhat small is nevertheless statistically significant at the 5% level of significance.[30]

The results suggest that the role of inventories is much bigger. Increasing the inventories to total assets ratio from the 25th to the 75th sample percentile would lead to a 28.5% increase in the accounts payable to assets ratio. The direction of this effect is consistent with Shleifer and Vishny's theory of the liquidation value. The collateral value increases with increasing inventories, which leads to an increased amount of trade credit supplied to the firm.

The coefficient on retained earnings is negative, and insignificant.[31] It is also very small relative to the other estimated coefficients. The small magnitude comes as no surprise, since there could very well be two effects cancelling out each other. The result provides some support for the pecking order theory, which suggests a negative relationship between a firm's retained earnings and its demand for trade credit. Even though this effect seems to dominate it appears to be partly offset by the positive effect of lower risk on the supply of trade credit, which is also associated with higher retained earnings.

There does not seem to be much influence on the amount of trade credit from the size and age of the potential recipient. Accounts payable appear to decline with increasing size, however the estimate lacks statistical significance. Again, it is possible that there are two effects present working in opposite directions. Lower demand for credit due to declining investment opportunities for older and larger firms can be offset by an increased supply of credit caused by a lower default risk commonly attributed to more established firms.

The estimate on the effect of market interest rate, represented in my regressions by the 3-month treasury bill, is perhaps the most consistent across specifications in my analysis. The coefficient on the T-Bill is highly significant and appears to be somewhat small, however, only until one recognizes the large variation in this interest rate over the sample period. Going from the 25th to the 75th sample percentile in this case means going from 4.41% to 7.46% interest rate, which is estimated to increase the accounts payable to assets ratio by roughly 3.7%. This finding is consistent with the transaction cost theory of trade credit.

The coefficient on change in sales suggests that faster growing firms demand more trade credit as their investment opportunities grow faster. This effect is smaller for firms with negative growth rates, nevertheless still positive. Petersen and Rajan (1997) also find this effect positive for firms with growing sales, however for firms with declining sales they find this effect negative.

Increasing profit causes firms to demand less trade credit due to higher cash flows, again according to the pecking order theory. This proposition is supported strongly by my results, even though the size of the effect is not very large. Increasing the net profit ratio (when profits are positive), going again from the 25th to the 75th sample percentile (from -0.005 to 0.021) decreases the payables to assets ratio by only around 0.7%.

The coefficient on the fraction of total assets in the form of current assets (excluding cash) confirms strongly that firms with more current assets use more trade credit.

4.2.2 Instrumented Pooled OLS and Fixed Effects

Table 2.5 lists results from the *instrumented* pooled OLS and the *instrumented* fixed effects regressions in the last two columns.[32] For comparison, the second and third columns of the table present results from the non-instrumented regressions, however this time re-estimated on the estimation sample from the instrumented versions. Note that more than half of the observations disappear because of missing data on tariffs.

Comparing table 2.5 with the previously discussed table 2.4, the values of the estimated coefficients seem to be fairly robust across the four estimation techniques used, while their significance is reduced greatly.[33] As discussed earlier, when describing the instrument, there are two possible explanations for the loss in significance. On the one hand, the missing data could have resulted in less precision in the estimation. This explanation may seem particularly plausible, because even the non-instrumented fixed effects model provides an insignificant coefficient on comovement with the reduced sample (see the first row of the fixed effects column in table 2.5). Alternatively, if comovement is endogenous, then the results from table 2.4 are invalid and the evidence that comovement affects the credit position of a firm is very weak.

5 Conclusion

In this chapter, I tested the effect of comovement of firms within an industry via its effect on the liquidation value of firms' assets, on the amount of trade credit supplied to a firm inside the industry. In the baseline specification, I found evidence that higher comovement leads to a lower amount of trade credit extended to the firm. Even though the effect of comovement on accounts payable is much smaller than the effect of inventories, it is statistically significant and larger in magnitude than the effect of profitability. This finding rests on the assumption that comovement is exogenous. When tariff is used as an instrument for comovement, the evidence is much weaker.

Notes

[1]See Harris and Raviv (1991) for a survey of theoretical research matched with the available empirical evidence. For a more recent survey of the empirical evidence see Rajan and Zingales (1995).

[2]In fact, MacKay and Phillips (2005) find, based on their sample of 315 competitive manufacturing industries, that only 13% of variation in financial structure can be attributed to industry fixed effects, while the rest of the variation can be attributed to firm fixed effects (54%) and within-firm variation (33%).

[3]According to the model presented in Shleifer and Vishny (1992), the level of optimal leverage of a firm increases with increasing liquidation value of its assets. This effect was previously suggested for instance in Myers (1977) and Diamond (1991). However, there also exists an alternative view for the role of liquidation values which argues the opposite: higher liquidity will provide a greater flexibility enabling the borrower to substitute riskier assets once funds are obtained, and therefore exposes the lender to a greater risk of potential default causing the lender to withdraw funds. See for instance Jensen and Meckling (1976) for more details about this kind of risk to the lender.

[4]The focus on trade credit is explained later in this section.

[5]Pulvino (1998) however does not specifically address the issue of comovement in his paper.

[6]See Jensen and Meckling (1976) for a detailed explanation of the agency cost problem.

[7]Banks can also repossess and resell assets, however they will incur much higher cost of doing so than issuers of trade credit who already have existing means to resell the taken

assets. See Petersen and Rajan (1997) on this point.

[8]See Petersen and Rajan (1994) for evidence, or Smith (1987).

[9]Titman and Wessels (1988) identify two proxies for the firm's liquidation value, the ratio of inventories to total assets and the ratio of tangible assets to total assets. Also see Song and Philippatos (2004) for a more recent example of using inventories as a proxy of the collateral value.

[10]Comin and Mulani (2006) define comovement as: $FLcomovement_{i,\tau} = \sum_{j \neq i, j \in I_i} (s_{j\tau}/(1 - s_{i\tau}))Cov(g_{i\tau}{}_{t-4}^{t+5}, g_{j\tau}{}_{t-4}^{t+5}),$

where I indexes an industry sector, i firm, t time period, g real sales growth rate, and $s_{i\tau}$ share of firm i real sales in total real sales of the corresponding industry sector in period τ, and where $Cov(g_{i\tau}{}_{t-2}^{t+2}, g_{j\tau}{}_{t-2}^{t+2})$ is defined as the covariance between $\{g_{i,t-2}, g_{i,t-1}, g_{it}, g_{i,t+1}, g_{i,t+2}\}and\{g_{j,t-2}, g_{j,t-1}, g_{jt}, g_{j,t+1}, g_{j,t+2}\}$.

[11]There are minor differences in the impact of shocks on the cash flows of different firms, otherwise there would be nothing to distinguish the sellers of assets from the buyers in the model.

[12]Industry dummies are included in the OLS regressions. However, because they are time invariant, industry dummies cannot be included in the fixed effects regressions.

[13]See for instance Almazan and Molina (2005) or Molina and Preve (2006) for the same approach.

[14]As Petersen and Rajan (1997) points out, if the ratio of depreciation to total assets

does not vary too much, then excluding depreciation makes no fundamental difference to the estimation, since net income divided by assets will be proportionate to depreciation added to net income and divided by assets.

[15]See Shleifer and Vishny (1992) for the theory of the liquidation value of a firm. Alternatively, a positive relationship between the inventory stock and the amount of trade credit received may also be explained by the transaction cost theory. The theory implies that suppliers may extend credit when it is advantageous to separate the delivery schedule from the payment schedule. In other words, lower transaction cost may result if firms with high levels of inventories are not required to pay each time a delivery occurs. See Ferris (1981) for more details about the transaction cost theory.

[16]See Jensen and Meckling (1976).

[17]Compustat is used frequently in financial studies. As examples, see Molina and Preve (2006) or Opler and Titman (1994).

[18]See section 2.3. for a discussion of the implications of the absence of small firms.

[19]Even though Compustat states that the quarterly data on accounts payable are available from 1976:1, the data is actually available for a few years prior to 1976. Nevertheless, prior to 1975, disproportionately more data are available for the first three quarters than for the fourth.

[20]Accounting treatment of these firms is also different from other industries.

[21]All of these studies implicitly assume that missing and deleted values occur randomly in Compustat.

[22]Also, around 300 observations containing negative values for payables, assets, or sales were deleted. The number of observations with zero accounts payble in the sample period

was 3,618.

[23]This number holds for Pooled OLS when inventories and retained earnings are excluded. If these two variables are present in the estimation additionally around 10,000 observations are lost due to missing data.

[24]See for instance Almazan et al. (2007) for a more recent example of scaling capital structure determinants by assets.

[25]Testing for serial correlation after the static form of regression returns a t-statistic equal to 263 on the added lagged residual. After including 4 lags, the t-statistic on the added lagged residual declines to 74. The remaining serial correlation in the error should be partly due to the time invariant unobserved effect, that will be removed in the fixed effects estimation. The serial correlation is not a major problem since the standard errors are robust to it, however unless the idiosyncratic firm effect is removed the regressors may be correlated with the error term, which would invalidate the empirical results. I also reran the regressions including 1, 2, 3, and 5 lags. The main results, particularly the approximate magnitude and significance of the comovement coefficient were similar across these various specifications. In the case of firm age, the lags are omitted since the inclusion would introduce multicollinearity in the model.

[26]The data on tariff rates is only available for manufacturing, and comes from two sources. Data for the 1989-2001 period was made available by John Romalis, and is linked for example at www.nber.org/data. Data for the 1976-1989 comes from the Center for International Data at UC Davis and can be found at www.internationalata.org. Since the earlier period tariffs are measured by the 1972-SIC categories, while the later period tariffs are measured by the 1987-SIC categories, I used a file also made available by the center at

UC Davis to convert the 1972-SIC data to the 1987-SIC data.

[27]When running the reduced form regression using comovement as the dependent variable, controlling for 4 lags of tariff, the coefficient on tariff was equal to 0.002, with the p-value equal 0.008 on this coefficient. While significant, the size is not very large. The tariff rates are in percentages, ranging from 0 to 13.5% in the sample, with the median being 2.47%. Increasing tariff in an industry with the median comovement rate from the 25th to the 75th percentile would thus lower the comovement from 0.061 to 0.054. The joint test on the tariff together with all of its four lags results in the F-statistic equal to 10.12 giving a p-value of zero to four decimal places. When repeating this test with lags of comovement as the dependent variable, the resulting F-statistic on the instrument and its lags ranged from 7.1 to 9.34, again giving a zero p-value to four decimal places.

[28]Only contemporaneous coefficients are shown in the table. Results for all lags are given in appendix 2.

[29]See Petersen (2007) for a summary and frequency of the estimation approaches used in the finance literature. According to Petersen, the fixed effects approach is second to the Fama-MacBeth procedure, with OLS being used less frequently.

[30]The bootstrapped standard errors indicate significance at the 5% level, while the usual robust standard errors indicate even stronger significance.

[31]Insignificant once the standard error is adjusted for the presence of generated regressor.

[32]Again, only contemporaneous coefficients are shown in the table. Results for all lags can be found in appendix 2.

[33]Statistical significance measured based on the bootstrapped standard errors is lost for all regressors in the last column, while when measured based on the usual standard errors

significance is lost only for the comovement variable.

Table 2.1: Description of the Variables

Variable	Description
Trade Credit	$\log\left(\frac{AP}{ASSETS}\right)$, where AP is balance sheet quarterly data item 46, "accounts payable" (original source: Compustat), and where $ASSETS$ is balance sheet quarterly data item 44, "assets - total" (original source: Compustat)
Comovement	See equation 1 in section 2.2., where $g_{i,t}$ is the quarterly growth rate of real sales of firm i, where real sales is $\frac{SALES}{PPI}$, where $SALES$ is quarterly data item 2, "sales (net)" (original source: Compustat), and where PPI is the producer price index (original source: U.S. Department of Labor: Bureau of Labor Statistics)
Firm Size	$\log\left(\frac{ASSETS}{PPI}\right)$, where $ASSETS$ is balance sheet quarterly data item 44, "assets - total" (original source: Compustat), and where PPI is the producer price index (original source: U.S. Department of Labor: Bureau of Labor Statistics)
Profitability and Availability of Internal Funds	$\frac{PROFIT}{ASSETS}$ if $PROFIT > 0$, 0 otherwise, where $PROFIT$ is balance sheet quarterly data item 69, "net income (loss)" (original source: Compustat), and where $ASSETS$ is balance sheet quarterly data item 44, "assets - total" (original source: Compustat)
	$\frac{PROFIT}{ASSETS}$ if $(PROFIT < 0)\&(\Delta SALES > 0)$, 0 otherwise, where $PROFIT$ and $ASSETS$ is the same as above, and where the variable $\Delta SALES$ is as described in the "Rate of Growth" variable entry below
	$\frac{PROFIT}{ASSETS}$ if $(PROFIT < 0)\&(\Delta SALES < 0)$, 0 otherwise, where $PROFIT$ and $ASSETS$ is the same as above, and where the variable $\Delta SALES$ is as described in the "Rate of Growth" variable entry below
Availability of Internal Funds	$\frac{RETAINED\ EARNINGS}{ASSETS}$, where *RETAINED EARNINGS* is balance sheet quarterly data item 58, "retained earnings" (original source: Compustat), and where $ASSETS$ is quarterly data item 44, "assets - total" (original source: Compustat)
Rate of Growth	$\frac{\Delta SALES}{ASSETS}$ if $\Delta SALES > 0$, 0 otherwise, where $\Delta SALES$ is the first difference in $SALES_t/PPI_t$, where $SALES_t/PPI_t$ is as defined for the Comovement variable, and where $ASSETS$ is quarterly data item 44, "assets - total" (original source: Compustat)

Table 2.1 (continued)

Variable	Description
Rate of Growth	$\frac{\Delta SALES}{ASSETS}$ if $\Delta SALES < 0$, 0 otherwise, where $\Delta SALES$ is the first difference in $SALES_t/PPI_t$, where $SALES_t/PPI_t$ is as defined for the Comovement variable, and where $ASSETS$ is quarterly data item 44, "assets - total" (original source: Compustat)
Age	$\log(1+AGE)$, where AGE is the number of quarters the firm has been present in the Compustat database
	$[\log(1+AGE)]^2$, where AGE is the number of quarters the firm has been present in the Compustat database
Current Assets	$\frac{CURRENT\ ASSETS - CASH}{ASSETS}$, where $CURRENT\ ASSETS$ is balance sheet quarterly data item 40, "current assets - total" (original source: Compustat), where $CASH$ is balance sheet quarterly data item 36, "cash and short-term investments" (original source: Compustat), and where $ASSETS$ is defined as for the next variable
Inventory Stock	$\frac{INVENTORIES}{ASSETS}$, where $INVENTORIES$ is balance sheet quarterly data item 38, "inventories - total" (original source: Compustat), and where $ASSETS$ is balance sheet quarterly data item 44, "assets - total" (original source: Compustat)
Market Interest Rate	3-month treasury bill: secondary market rate (original source: board of governors of the Federal Reserve System)

Table 2.2: Summary Statistics

Time Period	Accounts Payable / Assets							
	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
1976:2-2004:3	0.083	0.114	0.373	0	0.006	0.482	82	374379
1976:2-1984:4	0.092	0.113	0.088	0	0.009	0.417	3.04	84497
1985:1-1994:4	0.083	0.115	0.457	0	0.006	0.468	82	147537
1995:1-2004:3	0.078	0.113	0.380	0	0.005	0.547	56.533	142345
Time Period	COMOVEMENT (R-squared from OLS of sales growth rate on time dummies)							
	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
1976:2-2004:3	0.061	0.131	0.170	0.001	0.003	0.775	1	374379
1976:2-1984:4	0.118	0.195	0.203	0.002	0.003	0.851	1	84497
1985:1-1994:4	0.055	0.122	0.162	0.001	0.004	0.775	1	147537
1995:1-2004:3	0.044	0.102	0.145	0.002	0.003	0.725	1	142345
Time Period	Real Book Value of Assets (using PPI, in millions of 1982 dollars)							
	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
1976:2-2004:3	107.924	1141.6	4469.2	0.001	0.856	18614	188651	374379
1976:2-1984:4	142.536	949.58	3022.5	0.034	1.491	12137	153343	84497
1985:1-1994:4	74.586	967.85	3635.9	0.001	0.701	16851	107337	147537
1995:1-2004:3	127.152	1435.65	5767.8	0.002	0.873	23167	188651	142345
Time Period	Net Profit / Assets							
	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
1976:2-2004:3	0.010	-0.006	0.187	-47.667	-0.351	0.095	24.13	374397
1976:2-1984:4	0.014	0.010	0.058	-6.101	-0.141	0.073	5.007	84497
1985:1-1994:4	0.009	-0.004	0.130	-18	-0.321	0.102	8.069	147537
1995:1-2004:3	0.007	-0.018	0.268	-47.667	-0.469	0.102	24.13	142345

Notes:

When the comovement equals one it is because there was only 1 firm present in the industry during the 10 quarter window (these observations are not used in estimation). For each variable, median, minimum, 1st percentile, 99th percentile, and maximum are listed in the table.

Table 2.2 (continued)

Time Period	Change in Real Sales / Assets (Real Sales in millions of 1982 dollars, using PPI)							
	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
1976:2-2004:3	0.004	0.004	0.226	-114.55	-0.308	0.295	27.33	374379
1976:2-1984:4	0.004	0.004	0.099	-1.313	-0.316	0.288	5.192	84497
1985:1-1994:4	0.004	0.005	0.316	-114.55	-0.306	0.304	7.686	147537
1995:1-2004:3	0.004	0.004	0.157	-12.82	-0.303	0.288	27.32	142345
Time Period	**Age (Approximated by number of quarters since first appearance in Compustat)**							
	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
1976:2-2004:3	32	39.67	29.16	0	3	121	133	374379
1976:2-1984:4	27	26.40	14.71	0	2	53	60	84497
1985:1-1994:4	31	37.48	25.36	0	3	92	100	147537
1995:1-2004:3	43	49.83	35.06	0	4	125	133	142345
Time Period	**(Current Assets Less Cash) / Assets**							
	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
1976:2-2004:3	0.386	0.390	0.233	0	0.022	0.889	1	374379
1976:2-1984:4	0.460	0.434	0.229	0	0.039	0.878	0.992	84497
1985:1-1994:4	0.396	0.396	0.238	0	0.023	0.896	1	147537
1995:1-2004:3	0.340	0.357	0.226	0	0.017	0.883	1	142345

Notes:

For each variable, median, minimum, 1st percentile, 99th percentile,and maximum are listed in the table.

Table 2.3: Comovement by 2-digit SIC (full sample)

2-digit SIC	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
1	0.045	0.057	0.049	0.010	0.010	0.255	0.258	1147
2	0.195	0.191	0.082	0.051	0.051	0.383	0.383	114
7	0.181	0.258	0.176	0.068	0.068	0.817	0.817	262
8	0.228	0.247	0.063	0.145	0.145	0.361	0.361	59
10	0.028	0.078	0.121	0.007	0.009	0.532	1	3429
12	0.191	0.229	0.140	0.034	0.056	0.651	1	594
13	0.004	0.020	0.040	0.001	0.002	0.190	0.449	20511
14	0.091	0.122	0.091	0.034	0.035	0.373	0.374	832
15	0.034	0.073	0.102	0.007	0.008	0.447	1	4144
16	0.115	0.139	0.081	0.052	0.053	0.393	0.431	1796
17	0.087	0.129	0.101	0.030	0.043	0.548	0.670	1502
20	0.127	0.185	0.170	0.019	0.029	1	1	12077
21	0.284	0.352	0.180	0.133	0.136	0.879	0.908	665
22	0.148	0.164	0.088	0.025	0.034	0.441	0.718	4730
23	0.068	0.102	0.096	0.004	0.004	0.463	0.773	5506
24	0.248	0.257	0.143	0.049	0.051	0.586	1	3590
25	0.142	0.188	0.158	0.015	0.030	0.805	1	3689
26	0.065	0.109	0.130	0.014	0.016	0.738	1	6199
27	0.104	0.158	0.162	0.015	0.017	0.793	1	7930
28	0.028	0.055	0.080	0.003	0.004	0.343	1	29473
29	0.057	0.123	0.190	0.019	0.020	0.844	1	4096
30	0.085	0.119	0.126	0.008	0.012	0.617	0.950	7175
31	0.117	0.134	0.086	0.039	0.042	0.439	0.524	1943
32	0.305	0.331	0.212	0.027	0.031	1	1	4186
33	0.107	0.149	0.146	0.014	0.017	0.845	1	8555
34	0.103	0.150	0.140	0.006	0.017	0.740	1	10214
35	0.056	0.085	0.098	0.006	0.010	0.512	1	33371
36	0.023	0.056	0.090	0.003	0.005	0.469	1	37634
37	0.092	0.133	0.148	0.011	0.015	1	1	12055
38	0.024	0.051	0.087	0.005	0.005	0.444	1	29775
39	0.097	0.167	0.174	0.016	0.021	0.914	1	5668

Notes:
When the comovement equals one it is because there was only 1 firm present in the industry during the 10 quarter window (these observations are not used in estimation). For each variable, median, minimum, 1st percentile, 99th percentile, and maximum are listed in the table.

Table 2.3 (continued)

2-digit SIC	Median	Mean	Std Dev	Min	1stP	99thP	Max	Obs
40	0.057	0.093	0.136	0.029	0.029	1	1	2276
41	0.189	0.202	0.093	0.051	0.051	0.403	0.406	230
42	0.091	0.113	0.086	0.027	0.029	0.406	0.949	3737
44	0.067	0.096	0.113	0.018	0.019	0.995	1	1588
45	0.107	0.129	0.127	0.016	0.016	0.807	1	4032
46	0.228	0.203	0.099	0.066	0.066	0.393	0.399	117
47	0.079	0.106	0.090	0.023	0.026	0.482	0.535	1555
48	0.017	0.043	0.083	0.003	0.003	0.407	1	16366
49	0.297	0.337	0.229	0.015	0.026	0.800	1	33371
50	0.075	0.139	0.167	0.009	0.014	1	1	13810
51	0.076	0.112	0.107	0.015	0.019	0.490	1	8030
52	0.322	0.312	0.165	0.050	0.050	0.631	0.997	1451
53	0.608	0.579	0.186	0.094	0.101	0.852	0.978	4476
54	0.068	0.098	0.116	0.010	0.010	0.650	0.936	4691
55	0.142	0.195	0.168	0.036	0.036	1	1	1482
56	0.348	0.348	0.143	0.030	0.033	0.694	0.723	4194
57	0.324	0.371	0.203	0.058	0.065	0.907	0.955	2817
58	0.008	0.023	0.047	0.005	0.006	0.255	0.765	8600
59	0.078	0.175	0.187	0.011	0.012	0.800	0.894	9027
All	0.061	0.131	0.170	0.001	0.003	0.775	1	374379

Notes:
When the comovement equals one it is because there was only 1 firm present in the industry during the 10 quarter window (these observations are not used in estimation). For each variable, median, minimum, 1st percentile, 99th percentile, and maximum are listed in the table.

Table 2.4: Baseline Results

	Pooled OLS	Fixed Effects
	$\log\left(\frac{AP}{Assets}\right)$	$\log\left(\frac{AP}{Assets}\right)$
Comovement	-0.118*** ooo	-0.098*** oo
	(0.0394) [0.0455]	(0.0329) [0.0384]
log (book value of assets)	-0.005	-0.019
	(0.0277) [0.0400]	(0.0203) [0.0264]
Net Profit/Assets, if profit> 0	-0.235*** ooo	-0.121*** oo
	(0.0495) [0.0821]	(0.0305) [0.0538]
Net Profit/Assets, if profit<0 & Δsales> 0	-0.420*** oo	-0.340*** ooo
	(0.1213) [0.1692]	(0.0889) [0.1129]
Net Profit/Assets, if profit<0 & Δsales<0	-0.390*** oo	-0.284*** oo
	(0.1074) [0.1688]	(0.0844) [0.1332]
Δsales/Assets, if positive, 0 otherwise	0.614*** ooo	0.419*** ooo
	(0.1738) [0.2057]	(0.1207) [0.1397]
Δsales/Assets, if negative, 0 otherwise	0.103*	0.202*** ooo
	(0.0623) [0.1283]	(0.0381) [0.0730]
log (1+firm age)	-0.101**	0.117
	(0.0505) [0.0709]	(0.1014) [0.1309]
[log (1+firm age)]^2	0.016**	-0.013
	(0.0078) [0.0113]	(0.0217) [0.0278]
(Current Assets-Cash)/Assets	1.741*** ooo	1.676*** ooo
	(0.0705) [0.1098]	(0.0538) [0.0739]
Inventories / Assets	0.739*** ooo	0.762*** ooo
	(0.0924) [0.1233]	(0.0743) [0.1026]
Ret.Earnings / Assets	-0.001*	-0.002***
	(0.0007) [0.0051]	(0.0004) [0.0043]
T-Bill	0.011*** ooo	0.012*** ooo
	(0.0010) [0.0017]	(0.0009) [0.0016]
4 Lags of Regressors Included	Yes	Yes
Year and Quarter Dummies	Yes	Yes
4-digit SIC Industry Dummies	Yes	No

Table 2.4 (continued)

	Pooled OLS	Fixed Effects
	$\log\left(\frac{AP}{Assets}\right)$	$\log\left(\frac{AP}{Assets}\right)$
R-squared	0.47	0.26
Obs	280512	280512
Firms	9369	9369

Notes:

Standard errors in parentheses are robust to heteroskedasticity and serial correlation. Standard errors in brackets are bootstrapped and valid despite the presence of the generated regressor (comovement variable). Estimation assumes independence across firms. ***, **, and * denote respective significance at 1%, 5%,and 10% based on the standard errors given in parentheses. ^{ooo}, ^{oo}, and ^{o} denote respective significance at 1%, 5%,and 10% based on the standard errors
given in brackets. Firm age is approximated by the number of quarters present in the Compustat database. 4 lags are included for all individually listed regressors except age.

Table 2.5: Instrumental Variables

	Pooled OLS	Fixed Effects	2 SLS	FE-IV
	$\log\left(\frac{AP}{Assets}\right)$	$\log\left(\frac{AP}{Assets}\right)$	$\log\left(\frac{AP}{Assets}\right)$	$\log\left(\frac{AP}{Assets}\right)$
Comovement	-0.138* ^{oo} (0.0758) [0.0581]	-0.007 (0.0663) [0.0606]	-0.930 (6.5204) [30.50]	-2.537 (5.6860) [86.69]
log (book value of assets)	-0.008 (0.0331) [0.0487]	-0.021 (0.0254) [0.0384]	-0.020 (0.0350) [0.1313]	-0.027 (0.0273) [0.2405]
Net Profit/Assets, if profit>0	-0.369*** ^{ooo} (0.1004) [0.1383]	-0.186*** ^{o} (0.0697) [0.1081]	-0.366*** (0.1052) [0.3302]	-0.165** (0.0731) [0.7521]
Net Profit/Assets, if profit<0 & Δsales>0	-0.709*** ^{ooo} (0.0913) [0.1264]	-0.526*** ^{ooo} (0.0735) [0.1082]	-0.726*** ^{ooo} (0.0953) [0.1518]	-0.536*** (0.0764) [0.4281]
Net Profit/Assets, if profit<0 & Δsales<0	-0.689*** ^{ooo} (0.0888) [0.1393]	-0.563*** ^{ooo} (0.0796) [0.1148]	-0.696*** ^{ooo} (0.0923) [0.1353]	-0.568*** (0.0803) [0.5873]
Δsales/Assets, if positive, 0 otherwise	0.420 (0.3108) [0.4496]	0.292 (0.2103) [0.3068]	0.427 (0.3192) [0.4874]	0.295 (0.2146) [0.6860]
Δsales/Assets, if negative, 0 otherwise	0.154 (0.1054) [0.1493]	0.285*** ^{ooo} (0.0672) [0.1008]	0.129 (0.1117) [0.2768]	0.271*** (0.0752) [2.718]
log (1+firm age)	-0.109 (0.0781) [0.0914]	-0.150 (0.1487) [0.2030]	-0.097 (0.0818) [0.3705]	-0.167 (0.1615) [2.818]
[log (1+firm age)]^2	0.016 (0.0122) [0.0144]	0.041 (0.0326) [0.0454]	0.012 (0.0131) [0.0625]	0.044 (0.0351) [0.8481]
(Current Assets-Cash)/Assets	1.804*** ^{ooo} (0.1192) [0.1732]	1.696*** ^{ooo} (0.0813) [0.1149]	1.802*** ^{ooo} (0.1275) [0.3465]	1.711*** (0.0904) [1.197]
Inventories / Assets	0.678*** ^{ooo} (0.1526) [0.2113]	0.697*** ^{ooo} (0.1107) [0.1441]	0.645*** (0.1614) [0.4820]	0.660*** (0.1181) [2.538]
Ret.Earnings / Assets	-0.005*** (0.0020) [0.0163]	-0.003** (0.0014) [0.0151]	-0.005*** (0.0020) [0.0163]	-0.003** (0.0013) [0.0181]
T-Bill	0.015*** ^{ooo} (0.0016) [0.0024]	0.014*** ^{ooo} (0.0014) [0.0021]	0.025*** (0.0078) [0.0411]	0.019*** (0.0057) [0.1325]
4 Lags of Regressors Included	Yes	Yes	Yes	Yes
Year and Quarter Dummies	Yes	Yes	Yes	Yes
4-digit SIC Industry Dummies	Yes	No	Yes	No

Table 2.5 (continued)

	Pooled OLS	Fixed Effects	2 SLS	FE-IV
	$\log\left(\frac{AP}{Assets}\right)$	$\log\left(\frac{AP}{Assets}\right)$	$\log\left(\frac{AP}{Assets}\right)$	$\log\left(\frac{AP}{Assets}\right)$
R-squared	0.40	0.18	0.22	0.15
Obs	107965	107965	107965	107965
Firms	3798	3798	3798	3798

Notes:
Tariff is used as instrument for comovement in the last 2 columns. Standard errors in parentheses are robust to heteroskedasticity and serial correlation. Standard errors in brackets are bootstrapped and valid despite the presence of the generated regressor (comovement variable). Estimation assumes independence across firms. ***, **, and * denote respective significance at 1%, 5%,and 10% based on the standard errors given in parentheses. ^{ooo}, ^{oo}, and ^{o} denote respective significance at 1%, 5%,and 10% based on the standard errors given in brackets. Firm age is approximated by the number of quarters present in the Compustat database. 4 lags are included for all individually listed regressors except age.

Chapter 3: How Should We Control For the Clustering in Central Bank Intervention Data?

1 Introduction

Periods of sterilized central bank intervention in the foreign exchange market are intriguing episodes in the monetary history of countries.[1] Unlike the consensus amongst macroeconomists that a monetary policy action exhibits a real effect on output at least in the short run, there is little consensus that intervention has an effect on exchange rates or market volatility in the short or long run.[2] Looking at volume effects alone, it would be hard to make a case that intervention could influence exchange rates by shifting the supply or demand curve for foreign currency. For example, the largest magnitude of intervention in the DM/$ market in the 1980s was $1.3 billion, compared with total activity in the DM/$ market of $1,300 billion. Also, the Federal Reserve has intervened at times in amounts as little as $50 million. Thus, such interventions are only a tiny fraction of total market activity. Yet, all central bankers surveyed by Neely (2001) believe that intervention is effective in altering the exchange rate.

Another intriguing aspect of sterilized intervention is that the data is "clustered", with successive days of intervention followed by successive days without intervention. This clustering has been dealt with in many ways in the intervention literature. For example, Herrera and Ozbay (2005) estimate a dynamic Tobit model that includes lags of purchase and sale interventions (which are the dependent variables) for intervention by the Turkish

Central Bank in support of the Lira. Lagging the intervention variable has been pursued by Kim and Sheen (2002) and Frenkel, Pierdzioch and Stadtmann (2003) for the Australian and Japanese central banks respectively. Ito (2002) includes lags of the dependent intervention variable in a standard OLS regression for the Bank of Japan reaction function, or the function that predicts whether or not an intervention will occur on a given day.

The goal of this chapter is to determine what motivations trigger a central bank intervention, making use of two models that are specifically designed to exploit its data clustering; the autoregressive conditional hazard model (ACH, Hamilton and Jordà, 2002) and the autoregressive conditional binomial model (ACB, Herrera, 2004). We utilize two intervention data sets from three central banks. The first data set consists of interventions by the United States Federal Reserve and German Bundesbank between January 5th, 1987 and January 22nd, 1993. These dates coincide with the Plaza Agreement and the Louvre Accord. The second data set contains unilateral interventions by the Bank of Japan between April 1st, 1991 and February 28, 2001.

The ACH model modifies Engle and Russell's (1998) autoregressive conditional duration (ACD) model by estimating a $\{0,1\}$ Bernoulli process in calendar time and allowing for the inclusion of exogenous variables. The ACH model exploits the clustering by including a lag of the duration, or time between successive interventions, in the central bank's reaction function and uses the lagged duration to impose a functional form assumption on the conditional probability. That is, the ACH assumes the probability of intervention is equal to the reciprocal of the expected duration. For example, if the expected duration is 3, the probability of intervention is 1/3. The appeal is that Hamilton and Jordà, using an ACH model, are able to outperform a standard vector autoregression in terms of mean-squared error in predicting Federal funds rate target changes for the time period 1984-1989 and 1989-2001. This is a noteworthy result because, unlike a vector autoregression, the ACH maximizes a likelihood function rather than minimizing the sum of squared errors. Since open market operations exhibit similar clustering, it is natural to apply the ACH model to intervention data.

The ACB is a calendar time modification of the autoregressive conditional multinomial model of Engle and Russell (2005). The ACB exploits the clustering by lagging an indicator variable that takes the value of unity if an intervention occurred and lagging the response probability of intervention. In fact, the ACB without including the aforementioned lags is a standard probit model. Like the ACH model, exogenous variables can be included in the ACB model. Since the ACH and ACB are similar in that they are calendar time modifications of Engle and Russell models that are designed to exploit a common characteristic of time series data, the comparison done in this paper is a natural one. By comparing these two models, we can learn whether the time dependence in the data stems from durations, past probabilities of intervention, and/or past events. Thus, not only are the results relevant for this application, but they are relevant for other applications using similarly clustered data.

Surprisingly, in the case of the Federal Reserve, the ACH does worse, according to the Schwarz Bayesian Criterion (SBC, Schwarz, 1978) and the *pseudo* R^2 (McFadden, 1974), than a simple probit model that does not deal with the clustering. We show that this is likely due to the functional form imposed by the ACH for the estimated probability. For the Federal Reserve, the lagged duration is very insignificant in a probit model, meaning the ACH imposes its functional form assumption on an insignificant variable. For the other two central banks, the duration is significant, or nearly so in a probit model. Yet, the ACH only slightly improves the goodness-of-fit compared to a probit model and offers little additional insight as to why the central bank intervenes. And, surprisingly, the ACH can only successfully predict less than 1% of interventions.

Contrast this with the ACB, which outperforms the ACH for all central banks in terms of the SBC and the *pseudo* R^2. Unlike the probit and ACH, the ACB can successfully predict between 30% and 50% of interventions. A Rivers and Vuong (2002) test of non-nested likelihoods rejects the ACH in favor of the ACB for all central banks and a fluctuation test proposed by Giacomini and Rossi (2007) illustrates this preference is stable throughout the sample. Additionally, when the lagged duration is significant in a probit model, and dynamics are introduced in the ACB model, the significance of the lagged duration disappears. This suggests that the time dynamics are better captured through past probabilities and past events, rather than through past durations. As a result, we argue that an ACB model should be the first considered over an offshoot of an autoregressive conditional duration model (such as the ACH) when estimating a binary model with clustered data.

In utilizing the ACB to test motivations for intervention implied by the Plaza Agreement and Louvre Accord and emphasized in Neely (2001), we find some evidence of the Bundesbank intervening in order to move the exchange rate into line with long-run fundamentals, but the Federal Reserve did not. Interestingly, we find that both the Federal Reserve and Bundesbank preferred to intervene when foreign exchange market volatility was low, rather than intervening when volatility was high with the goal of reducing it. We show a novel result in that the spread between the six month Treasury Bill rate and the Federal Funds rate contains predictive power as to when the Federal Reserve will intervene, suggesting a link between Federal Reserve monetary policy and intervention. As far as we know, neither of these two results have been shown in the intervention literature using daily data. We find strong evidence that the Bank of Japan has intervened in response to day-by-day changes in the nominal ¥/$ exchange rate and evidence that this response is different following Eisuke Sakakibara becoming the Director General of the International Finance Bureau of the Ministry of Finance in Japan on June 1st, 1995.[3] Intervention by the Bank of Japan can be described as "leaning against the wind" prior to Sakakibara's appointment and can be described as "leaning with the wind" following his appointment.[4]

The remainder of this chapter is organized as follows. Section 2 describes the intervention data. Section 3 describes modeling the probability of intervention using the ACH and ACB. Section 4 presents the results. Section 5 offers a comparison of the two econometric methods, and Section 6 concludes.

2 Intervention Data

2.1 U.S. and Germany

We use daily weekday intervention and exchange rate data for the Federal Reserve and Bundesbank interventions in the DM/$ market spanning January 5th, 1987 through January 22nd, 1993, which corresponds to 1387 observations.[5] Thus, the data follows the Plaza Agreement (signed September 22, 1985) and the Louvre Accord (signed February 22nd, 1987). The goal of the Plaza Agreement was to use coordinated intervention to depreciate the dollar against its main trading currencies in hopes of reducing the U.S. current account deficit and quelling protectionist pressure in the U.S. Congress.[6] Since the dollar had substantially depreciated against both the dollar and yen following the Plaza Agreement, the goal of the Louvre Accord was market stability.[7] Nigel Lawson, British Chancellor of the Exchequer, called the meeting "Plaza Two [...] I see this meeting as the lineal descendent of the Plaza meeting [...]Then we all agreed that the dollar should fall, now we all agree we need stability."[8]

Table 3.1 presents summary statistics on the Federal Reserve and German intervention data sets. Note that the Federal Reserve only intervened 173 times during the sample period, or in 12.5% of the observations. The Bundesbank intervened more, 210 times, or 14.3% of the observations. Dollar buys were observed on 65 days for the Federal Reserve, accounting for 37.6% of Federal Reserve interventions, and on 55 days for the Bundesbank, corresponding to 26.1% of Bundesbank interventions. Compare this to dollar sales, which were observed on 108 days for the Federal Reserve, corresponding to 62.4% of Federal Reserve interventions, and on 155 days for the Bundesbank, corresponding to 73.8% of Bundesbank interventions. Thus, the vast majority of interventions by the Federal Reserve and Bundesbank taking the form of dollar sales is consistent with the goal of the Plaza Agreement to depreciate the dollar against the Deutsche mark.

Table 3.1 also gives evidence to the clustering present in the intervention data for both the Federal Reserve and the Bundesbank. For instance, for the Federal Reserve, only 13.3% of interventions took place in weeks with only one intervention whereas 29.5% of interventions took place in weeks with two interventions. Not only do interventions take place for only a small percentage of observations, but the vast majority of interventions take place in weeks with multiple interventions. Note from the table that the clustering is similar for the Bundesbank. Figure 3.1 gives a graphical representation of the clustering for the Federal Reserve.[9] This clustering is what we are trying to exploit using the ACH and ACB.

2.2 Japan

We use daily weekday intervention data for the Bank of Japan interventions in the Tokyo ¥/$ market spanning April 1st, 1991 through February 28, 2001, which corresponds to 2538 observations and overlaps with the data in Ito (2002).[10]

Table 3.2 presents summary statistics on the Japanese intervention data set. The Bank of Japan intervened in 200 days in time span covered by the data, which corresponds to 7.8% of the observations. Yen buys were observed on 32 days or 16% of the interventions, while yen sales were observed on 168 days or 84% of the interventions. This is consistent with the Japanese goal of depreciating the yen through intervention, as an overvalued yen made Japan's vital export sector less competitive (Ito, 2002). Note that the smallest yen buys and sells were ¥3.2 billion and ¥5.1 billion respectively. This corresponds to a buy of $25.1 million and a sale of $45.1 million, using the spot ¥/$ exchange rate for those days. Thus, Japanese intervention data is similar to the data for the Federal Reserve and Bundesbank in that interventions represent a small fraction of daily market activity.

Table 3.2 also breaks down the summary statistics into two subsamples, corresponding to intervention before and during Eisuke Sakakibara's tenure as Director General of the International Finance Bureau of the Ministry of Japan . Both Ito (2002) and Kearns and Rigobon (2004) note that the behavior of Japanese intervention changed with Sakakibara's appointment, which began on June 1st, 1995. Whereas intervention behavior prior to Sakakibara was to resist short-term undesirable movements in the exchange rate (or to "lean against the wind"), intervention during Sakakibara's tenure was to actively move the yen back to the desired range by "leaning with the wind". For example, if the goal was to depreciate the yen, and the yen began to depreciate the foreign exchange market on its own, Sakakibara would intervene by selling yen with the goal of further depreciating it.

Two things are noteworthy about the different subsamples. First, intervention was much more frequent in the first subsample than in the second. Second, intervention was much smaller in average magnitude in the first subsample than in the second. Notice that for the entire sample, the smallest yen buys and sells took place during the first subsample while the largest buys and sells took place during the second subsample. Also, note that the magnitude of the largest buy in the first subsample (¥76.9 billion) is nearly the same as the smallest buy in the second subsample (¥76.4 billion). The reason for these differences between the two subsamples is that Sakakibara believed that the market was becoming too accustomed to the smaller, more frequent interventions of the preceding regime. Sakakibara believed that by reducing the frequency and increasing the magnitude of intervention, he could more successfully depreciate the yen against the dollar.[11]

Table 3.2 presents evidence of the clustering of interventions both in the full sample and in the two subsamples. For the full sample, only 22% of interventions took place in weeks with only one intervention; 18% of interventions took place in weeks with two interventions; 22.5% of interventions took place in weeks with three interventions; 20% of interventions took place in weeks with four interventions and 17.5% of interventions took place in weeks with five interventions. Figure 3.2 presents a graphical representation of the clustering for the full sample of the Bank of Japan. Thus, similar to the Federal Reserve and the Bundesbank, observations with interventions represent a small fraction of the observations and the vast majority of the interventions occur in weeks with multiple interventions.

3 Estimating the Probability of Intervention

3.1 ACH

Following the notation of Engle and Russell (1998) and Hamilton and Jordà (2002), we define the variable u_i as the length of time between the i^{th} and $(i+1)^{th}$ intervention. Then we define ψ_i to be the expectation of u_i given past durations $u_{i-1}, u_{i-2}, \ldots$. Then, the ACD(r,m) model of Engle and Russell is:

$$\psi_i = \omega + \sum_{j=1}^{m} \alpha_j u_{i-j} + \sum_{j=1}^{r} \beta_j \psi_{i-j} \tag{1}$$

which is analogous to a GARCH(m,r) process. Thus, the ACD(1,1) model posits that the expected duration is a weighted average of past durations:

$$\psi_n = \alpha u_{n-1} + \beta \alpha u_{n-2} + \beta^2 \alpha u_{n-3} + \ldots + \beta^{n-2} \alpha u_1 + \beta^{n-1} \overline{u} \tag{2}$$

where $\overline{u}$ is the average duration. The parameter β controls how fast the past durations decay in predicting the n^{th} expected duration. Engle and Russell (1998) show that for the ACD(r,m) process to be stationary, $\sum_{j=1}^{m} \alpha_j + \sum_{j=1}^{r} \beta_j < 1$.

Following Hamilton and Jordà (2002), we transform the timing of the ACD model to calendar time. We define the function $N(t)$ as the cumulative number of interventions observed at time t. Thus, if we do not observe an intervention at time t, $N(t) = N(t-1)$. If we observe an intervention at time t, then $N(t) = N(t-1) + 1$. Using this notation, we can rewrite equation (1) as:[12]

$$\psi_{N(t)} = \sum_{j=1}^{m} \alpha_j u_{N(t)-j} + \sum_{j=1}^{r} \beta_j \psi_{N(t)-j} \tag{3}$$

The hazard rate, h_t, is defined as the conditional probability of an intervention taking place at time $t-1$ given information observed as of time $t-1$. Thus, the hazard can be written as:

$$h_t = \Pr\left[N(t) \neq N(t-1) \mid Y_{t-1}\right] \tag{4}$$

Where Y_{t-1} denotes information known as of time t. We follow Hamilton and Jordà (2002) and assume that the conditional distribution of the hazard is exponential. Under the exponential distribution, we can write the hazard for the ACH process as:[13]

$$h_t = \frac{1}{\psi_{N(t-1)} + \omega + \gamma' \mathbf{z}_{t-1}} \tag{5}$$

where ω is a constant and $\mathbf{z}_{t-1}$ is a vector of explanatory variables observed on the previous day. Thus, the ACH imposes the functional form that the probability of intervention is equal to the reciprocal of the expected duration, plus or minus some exogenous variables.

Defining the binary variable x_t, taking the value of unity if there is an intervention on date t, and zero otherwise, we can obtain estimates for the parameters $\theta = \left(\gamma', \alpha', \beta'\right)'$ by maximizing the likelihood function:

$$\sum_{t=1}^{T} \{x_t \log(h_t) + (1 - x_t) \log(1 - h_t)\} \tag{6}$$

3.2 ACB

The ACB model is a flexible specification that captures the intervention clustering by lagging the link function and binary dependent variable. First, define the probability of an intervention as,

$$h_t \equiv P\left(x_t = 1 \mid x_{t-1}, ..., x_1, \mathbf{z}_{t-1}, ..., \mathbf{z}_1\right) \tag{7}$$

where, as before, h_t is the probability of intervention, x_t is the binary dependent variable taking the value of unity if we observe an intervention, and $\mathbf{z}_{t-1}$ is a $1 \times n$ vector of exogenous variables that contain information about the underlying process. For our application, $\mathbf{z}_{t-1}$ will contain the same exogenous variables for both the ACB and the ACH. Additionally for the ACB, we include the lag of the duration, $u_{N(t-1)}$ in the $\mathbf{z}$ vector.[14]

The ACB(q,r,s) model is then given by,

$$G^{-1}(h_t) = \omega + \sum_{j=1}^{q} \eta_j \left(x_{t-j} - h_{t-j}\right) + \sum_{j=1}^{r} \rho_j G^{-1}\left(h_{t-j}\right) + \sum_{j=1}^{s} \delta_j x_{t-j} + \gamma \mathbf{z}_{t-1} \tag{8}$$

where $G(\cdot)$ is a strictly increasing, continuous cumulative distribution function, such as the standard normal or the logistic. Thus, $G^{-1}(h_{t-1}) = z_t \Leftrightarrow G(z_t) = h_t$, meaning that

$G^{-1}(\cdot)$ is a 1-1 mapping from h_t to $\Re$. Thus, the ACB exploits the clustering by allowing the current intervention decision to depend on the lagged response probability and the past history of interventions. Since $G(\cdot)$ is strictly increasing, we can obtain x_t by taking the inverse of equation (8),

$$h_t = G\left[\omega + \sum_{j=1}^{q} \eta_j \left(x_{t-j} - h_{t-j}\right) + \sum_{j=1}^{r} \rho_j G^{-1}\left(h_{t-j}\right) + \sum_{j=1}^{s} \delta_j x_{t-j} + \gamma \mathbf{z}_{t-1}\right] \quad (9)$$

Since we choose the standard normal distribution for $G(\cdot)$, the ACB(0,0,0) is simply a standard probit model. Thus, including the same exogenous variables in the $\mathbf{z}_{t-1}$vector in the ACH plus the lagged duration serves two purposes. First, comparing the ACH with the ACB(0,0,0) allows us to compare the functional form assumption imposed by the ACH versus the functional form of the probit. Second, introducing lags into the ACB(0,0,0) allows us to compare the lagged duration in capturing the time dynamics of the clustered data versus lags of $G^{-1}(h_t)$ and x_t.

Given initial conditions for x_t and h_t, the path of intervention probabilities can be constructed and estimates for the parameters $\theta = \{w, \eta_1, ..., \eta_q, \rho_1, ..., \rho_r, \delta_1, ..., \delta_s\}$ obtained. Estimation is straightforward through maximizing the likelihood function,

$$\sum_{t=\max\{q,r,s\}+1}^{T} \left[x_t \log(h_t) + (1 - x_t) \log(1 - h_t)\right] \tag{10}$$

3.3 Explanatory Variables

We appeal to the institutional background in deciding what explanatory variables to include in the **z** vector for each data set. For the U.S. and Germany, following the Plaza Agreement's declared goal that "exchange rates should better reflect fundamental economic conditions than has been the case",[15] we include a measure of the deviation of the log of the exchange rate, s_t, from the log of the exchange rate based on purchasing power parity, s_t^*, which is the exchange rate that would prevail based on economic fundamentals (Neely 2005). Absolute purchasing power parity is defined as:

$$S_t = \frac{P_t}{P_t^f} \tag{11}$$

where S_t is the level of the exchange rate, P_t is the price level in the U.S. and P_t^f is the price level in the foreign country. Taking the natural logarithm of both sides of equation (11),

$$s_t^* = p_t - p_t^f \tag{12}$$

Thus, the exchange rate based on economic fundamentals can be calculated by simply taking the difference of the log of the price level between the U.S. and Germany.[16]

Following the Louvre Accord's goal to calm disorderly markets, we include a measure of daily excess volatility as suggested by Baillie and Osterberg (1997). We define excess volatility as the difference between the conditional and unconditional variance of exchange rate returns, or $(\sigma_t^2 - \sigma^2)$. The conditional variance is generated through a GARCH(1,1) process for the log-difference of exchange rate returns:

$$\sigma_t^2 = \omega + \zeta \varepsilon_{t-1}^2 + \xi \sigma_{t-1}^2 \tag{13}$$

The unconditional variance can then be computed from equation (13):

$$\sigma = \frac{\omega}{1 - \zeta - \xi}$$

Fischer (2000) points out that a central bank's domestic monetary policy objective might be in conflict with current foreign exchange market conditions. For example, recall that the goal of the Plaza Agreement was to depreciate the dollar, which could be achieved by expansionary monetary policy.[17] However, if the Federal Reserve's domestic monetary policy objective at the time was restrictive rather than expansionary, restrictive monetary policy would appreciate the dollar. As a result, the Federal Reserve may postpone a change in monetary policy so that the exchange rate is not further undermined and confusing signals are not sent to the foreign exchange market (monetary policy in support of the dollar alongside intervention to depreciate the dollar). To examine the link between the Federal Reserve's monetary policy and intervention objectives we include in the **z** vector the absolute value of the spread between the 6-month Treasury Bill and the Federal funds rate.[18]

For Japan, rather than including the difference of the nominal logged exchange rate from fundamentals, we include the change in the natural log of the nominal exchange rate from date t to date $t - 1$.[19] This captures the idea that the Japanese intervened in response to overnight changes in the ¥/$ nominal exchange rate. Ito (2002) contains detailed accounts of many of the intervention episodes throughout the 1990s. In general, the Japanese wanted to keep the yen within a range of 128¥/$ to 115¥/$, buying yen when the nominal exchange rate crossed the upper limit and selling yen when it crossed the lower limit. However, in 1993, the yen fell out of this range and did not return until early 1997 (Ito, 2002). Thus, a motivation for Japanese intervention cannot be to defend this range, since the yen was not in, nor even close to it, for a large part of this sample. A more likely motivation is to lean against the wind, or resist short term movements in the nominal exchange rate. Ito (2002) is ripe with instances of this. For example, the intervention of February 15, 1994 was prompted by an overnight appreciation of the yen from 104¥/$ to 102¥/$.

Neither Ito (2002) nor Kearns and Rigobon (2004) explicitly model whether or not the Japanese intervened in response to excess market volatility with the goal of reducing it. However, Ito does imply that the Japanese may have intervened in response to excess market volatility in order to smooth the appreciation of the yen against the dollar. To test whether or not this was a motivation for Japanese intervention, we include the measure of conditional volatility given by equation (13).

4 Results

4.1 U.S. and Germany

The results for estimating the probability of intervention for the Federal Reserve using the ACH(1,1) model are reported in Table 3.3. Note that the estimated values for α and β are both significant at the 1% level. The ACH obtains an estimate of 4.701 for the average expected duration, meaning that on average, approximately 5 days are expected to pass between two interventions. This corresponds to an average hazard, or the average probability of an intervention occurring on a given day, of 0.0984. This is broadly consistent with the summary statistics in Table 3.1, where interventions happened for 12.47% of the observations

As seen from the table, there is mixed evidence on the predictive power of the two variables based on the Plaza Agreement and Louvre Accord as to when the Federal Reserve will intervene. The estimated coefficient on $(\sigma_{t-1}^2 - \sigma^2)$, which is the variable implied by the Louvre Accord, is insignificant, whereas the estimated coefficient on the first difference of $(s_{t-1} - s_{t-1}^*)$, which is the variable implied by the Plaza agreement, is significant at the 10% level. However, upon dropping $(\sigma_{t-1}^2 - \sigma^2)$ and re-estimating the ACH model (which we do in specification (2)), the first difference of $(s_{t-1} - s_{t-1}^*)$ becomes significant at the 5% level (p-value 0.0358). This is an interesting result because it suggests that the Federal Reserve is intervening as a result of the nominal DM/\$ exchange rate moving away from the exchange rate based on economic fundamentals.

To see this, note that if the dollar is overvalued as the U.S. claimed, then $(s_{t-1} - s_{t-1}^*) > 0$ and the estimated coefficient on this term in the ACH model is negative. Thus,

$\gamma_3 \Delta \left(s_{t-1} - s^*_{t-1}\right) < 0$. Notice from equation (5) that this term appears in the denominator of the hazard, which is the probability of intervention. Thus, this term being negative makes the denominator of the hazard smaller, which increases the probability of intervention.

The coefficient on the spread is negative and significant, suggesting that for a day where the absolute value of the spread between the 6-month Treasury Bill rate and the Federal funds rate is high, the probability of intervention by the Federal Reserve is higher than compared to a day when the absolute value of the spread is low.

These are novel results because, as far as we know, no study has established a statistical link between the value of the spread and the probability of intervention. Also, studies using the same data do not find the Federal Reserve responding to changes in the exchange rate (see, for example, Baillie and Osterberg 1997). Column 3 of Table 3.4 presents the results of a probit, or ACB(0,0,0) model, containing the same explanatory variables, including the lagged duration. Note that when we do not exploit the clustering via the ACH, we do not find the estimated coefficient on $\Delta \left(s_{t-1} - s^*_{t-1}\right)$ to be significant, though the estimated coefficient on spread is positive and significant, giving the same interpretation as before. Thus, it would appear that the ACH is offering a new result.

However, consider the estimates of the ACB model in Table 3.4.[20,21] Note that in this case, the estimated coefficient on $\Delta \left(s_{t-1} - s^*_{t-1}\right)$ fails to be significant at the 10% level, even though the sign is consistent with the result for the ACH(1,1), since it also suggests that a more overvalued dollar increases the probability of intervention. Also, notice the difference in the estimated coefficient on $\left(\sigma^2_{t-1} - \sigma^2\right)$. Whereas this was insignificant in the ACH and probit models, it is significant in the ACB(0,1,2) model. However, the negative sign indicates that low volatility increases the probability of intervention. Thus, the sign is the opposite of what we would expect from the Louvre Accord, meaning the Federal Reserve prefers to intervene when the market is calmer. Although this result is the opposite of the Federal Reserve's stated policy, studies that use ultra-high frequency data, such as Beine and Laurent (2003 and 2005), and Fatum (2002), find that intervention increases market volatility. As a result, the negative estimated sign on $(\sigma_{t-1}^2 - \sigma^2)$ suggests that the Federal Reserve would prefer not to make an already volatile market even more volatile through intervention. Thus, it is interesting that we are able to replicate this result with daily data using the dynamic binary model.

Notice that the spread continues to have positive predictive power for interventions, meaning that days when the spread is higher are days where the Federal Reserve is more likely to intervene. Two explanations can account for this robust result. First, suppose that the spread is large and positive, indicating that the market is expecting an increase in the Federal funds rate. As previously described, this would appreciate the dollar, which is in the opposite direction of the goal of the Plaza Agreement. Thus the sign and significance of the spread is consistent with the idea that the Federal Reserve may have to postpone this monetary policy action and instead use sterilized intervention to achieve its exchange rate objective.

The second explanation is consistent with the idea that the Federal Reserve's monetary policy objective during this time was expansionary, rather than restrictive. Consider when the Federal funds rate is above the 6-month Treasury Bill rate, as it is for the majority of our sample. The high value of the Federal funds rate relative to the Treasury Bill rate suggests that the market expected the Federal Reserve to engage in an expansionary monetary policy, producing a subsequent fall in the Federal funds rate, which would also depreciate the dollar against the Deutsche mark. However, as Funabashi (1989) points out, the Federal Reserve wanted to conduct expansionary monetary policy jointly with the Bundesbank. The Bundesbank was reluctant to do so, given its strong anti-inflationary bias and its reluctance to relinquish its independence in setting monetary policy. Thus, rather then engaging in expansionary monetary policy to depreciate the dollar, the Federal Reserve chose to engage in sterilized intervention instead. This is consistent with Funabashi (1989) who found that "The Fed used monetary policy to stimulate the U.S. economy or at least to keep it buoyant, but it did not burden domestic monetary policy with exchange rate management" (p57).

The results of the ACH(1,1) for Bundesbank intervention are reported in the last column of Table 3.3. The results are similar to those obtained in the case of the Federal Reserve in that α and β are both significant, albeit α is now significant at 5%, and the estimated coefficient on $\left(\sigma_{t-1}^2 - \sigma^2\right)$ is insignificant. One major difference between the two central banks is that the coefficient on $\Delta\left(s_{t-1} - s_{t-1}^*\right)$ is insignificant for the Bundesbank, although with the expected sign.[22]

Column 3 of Table 3.5 presents the results of the probit model. The estimates of the coefficients on $\left(\sigma_{t-1}^2 - \sigma^2\right)$ and $\Delta\left(s_{t-1} - s_{t-1}^*\right)$ are both insignificant as in the ACH case. We include $u_{N(t-1)}$ in the probit model and find that it is significant at the 5% level as in the case of the ACH, and in the same direction, also as in the ACH case.

However, like the Federal Reserve, the results are not robust to the ACB model. The last three columns of Table 3.5 present these results. Three interesting results are important to note. First γ_2, the estimated coefficient on $\Delta\left(s_{t-1} - s_{t-1}^*\right)$, is estimated to be positive and significant at the 1% level. Recall that if the dollar is overvalued then $\Delta\left(s_{t-1} - s^*_{t-1}\right) > 0$. Thus, a positive estimate of γ_3 means that the probability of intervention by the Bundesbank increases when the dollar becomes more overvalued. Second, when we exploit the clustering by introducing lags of the binary indicator x_{t-1} and the link function $G^{-1}(h_{t-1})$, the estimated coefficient on the lagged duration becomes insignificant. This suggests that including lags of the duration does not capture the time dynamics in the data. Third, like for the Federal Reserve, the estimated coefficient on $\left(\sigma^2_{t-1} - \sigma^2\right)$ is negative and significant, suggesting that the Bundesbank may prefer to intervene in times of low market volatility so that intervention does not make an already volatile market more volatile. Again, this result has recently been found in the literature using ultra-high frequency data. As far as we can tell, we are the first to find it using daily data.

4.2 Japan

Table 3.6 presents the results of the ACH(1,1) for the entire sample of Japanese intervention. Note that γ_2, which is the estimated coefficient on $(s_{t-1} - s_{t-2})$, is positive and significant, meaning that the Japanese were "leaning against the wind", or resisting short-term, overnight movements in the nominal exchange rate. Recall that the goal of Japan was to depreciate the yen against the dollar to improve the competitiveness of their exports, and that the exchange rate is in terms of yen per dollar. Thus, $(s_{t-1} - s_{t-2}) < 0$ means that yen appreciated $(s_{t-1} < s_{t-2})$. The positive estimated value of γ_2 thus makes $\gamma_2 (s_{t-1} - s_{t-2}) < 0$ and thus the denominator of equation (5) smaller.[23]

As with the Federal Reserve and Bundesbank, we compare the results of the ACH with those of the probit and dynamic ACB models. Column 3 of Table 3.7 presents the results of the probit for the entire sample. Here, we find a negative and significant estimate of γ_2, the coefficient on $(s_{t-1} - s_{t-2})$. Thus, the leaning against the wind behavior is robust to the probit specification, since $\gamma_2 (s_{t-1} - s_{t-2}) > 0$ following a yen appreciation, which increases the probability of intervention.

Columns 4-6 of Table 3.7 present the results of the ACB(0,1,3) model for Japan. Like the two previous models, the ACB(0,1,3) finds that the Japanese are leaning against the wind, with the estimated coefficient on $(s_{t-1} - s_{t-2})$ negative and significant. Note that $(\sigma^2_{t-1} - \sigma^2)$ is largely insignificant in all models (although it is significant at the 10% level in the ACB), suggesting that market volatility played little role in determining Japanese intervention, and that the Japanese were more concerned with the level of the nominal ¥/$ exchange rate.

To see how Japanese intervention differed before and after Sakakibara's tenure, we reestimate the ACH, probit, and ACB models before and after June 1, 1995. Columns 4 and 5 of Table 3.6 present the ACH results and Table 3.8 presents the ACB(0,1,2) results for the 1st subsample, which corresponds to intervention prior to Sakakibara. These results are very similar to the results for the entire sample. In each model, we find evidence for leaning against the wind.

However, contrast this with the results of the second subsample. Column 6 of Table 3.6 and Table 3.9 present the results of the second subsample. Note that these results are strikingly different than those for the entire sample and the first subsample. For each model, notice the sign change for the coefficient on $(s_{t-1} - s_{t-2})$. This suggests that after Sakakibara, the Japanese were leaning *with* the wind, or intervening in response to a favorable overnight movement in the exchange rate in order to further that movement. Note that if the yen depreciates, $(s_{t-1} - s_{t-2}) > 0$. Thus, the negative estimated coefficient in the ACH model means $\gamma_2 (s_{t-1} - s_{t-2}) < 0$, which makes the denominator of equation (5) smaller and thus the hazard larger. The positive estimated coefficient in the probit and ACB(0,1,2) means that $\gamma_2 (s_{t-1} - s_{t-2}) > 0$, which makes the probability of intervention larger. This evidence suggests that Sakakibara preferred to influence the exchange rate by intervening when market conditions were already moving in the direction he favored. That is, if the yen was depreciating, Sakakibara intervened to further depreciate it.

Compare and contrast these results of the two Japanese subsamples with what is found by Ito (2002). With our methodology, we find that the Japanese leaned against the wind prior to Sakakibara and leaned with the wind during Sakakibara's tenure. Ito, however, finds the lean against the wind hypothesis to be statistically insignificant during the first subsample but statistically significant during the second subsample. Ito also finds no evidence for leaning with the wind. Thus, we argue that our results are more consistent with Japanese intervention behavior. Ito finds that interventions in the second subsample were less predictable than in the first subsample given the lower R^2 in his second subsample regression than his first. Our result is similar. We find that interventions in the second subsample are less predictable than interventions in the first. Both the *pseudo* R^2 and percent of interventions correctly predicted are lower in the second subsample compared with the first. This is consistent with the idea that Sakakibara believed that Japanese interventions were too predictable, and consequently made them less so.

5 Comparison of Econometric Methods

5.1 Goodness-of-Fit

To begin a comparison between the ACH, probit, and ACB, we construct two measures of goodness-of-fit based on the log-likelihood of each model. The Schwarz Bayesian Criterion (SBC, Schwarz, 1978) adjusts the log-likelihood by subtracting $(r/2)$ times the natural log of of the number of observations, where r is the number of parameters estimated by the model. The *pseudo* R^2 suggested by McFadden (1974) is found by computing $1 - \mathcal{L}_{ur}/\mathcal{L}_o$, for each model, where $\mathcal{L}_{ur}$ is the unrestricted log-likelihood and $\mathcal{L}_o$ is the log-likelihood of the model under the restriction that all parameters except the constant are zero.

Both the SBC and *psudeo* R^2 are reported at the bottom of the table for each estimated model. Comparing Tables 3.3-3.5 for the Federal Reserve and Bundesbank, we see that the ACH is favored over the probit for the Bundesbank, which is expected, given the clustering present in the data. Yet, given this, the *pseudo* R^2 is relatively low, never getting above 0.10. Both measures are markedly different for the ACB. Both the log-likelihood and SBC drastically fall, and the *pseudo* R^2 rises from 0.04 for the Federal Reserve and 0.095 for the Bundesbank to around 0.3 for each. Finally, note that it is curious how neither measure favors the ACH over the probit for the Federal Reserve, since Table 3.2 and Figure 3.1 illustrate that the Federal Reserve data exhibits similar clustering to the Bundesbank.

Comparing Tables 3.6-3.7 for full-sample Japan, we see that the results are similar to those for the Bundesbank. The ACH is preferred to probit by both measures, but like before, the *pseudo* R^2 is relatively low. And, like with the Federal Reserve and Bundesbank, both measures strongly prefer the ACB to the other two models. The SBC falls, and the *pseudo* R^2 rises from 0.04 to 0.36 for the full Japanese sample. Thus, there is consistent evidence that the ACB fits the data better.

However, one may offer the criticism that since the log-likehood is much lower for the ACB, compared to the probit and ACH, goodness-of-fit measures relying on it will naturally prefer the ACB. To conduct a robustness check using a measure not relying on the log-likelihood, we compute the percentage of interventions correctly predicted (PCP) for each model.[24]

Comparing Tables 3.3-3.5 for the Federal Reserve and the Bundesbank, the results are troubling for the probit; it cannot successfully predict a single intervention for either central bank! Surprisingly, the results are just as troubling for the ACH. It cannot successfully predict a single intervention for the Federal Reserve and only successfully predicts 0.7% of them for the Bundesbank. However, like the goodness-of-fit measures relying on the log-likelihood, the ACB performs drastically better. It is able to successfully predict nearly half of the interventions for both central banks. The PCP for Japan is largely the same (see Tables 3.6-3.9).

Figures 3.3 and 3.4 illustrate above result for the Federal Reserve. Figure 3.3 prints out the probit and ACH estimated probability of intervention. Notice that neither model ever assigns a probability for intervention over 0.50.[25] Since a probability of at least 0.50 is the standard criteria for predicting an event (see, for example, Wooldridge 2002), neither model predicts that an intervention will occur. Contrast Figure 3.3 with Figure 3.4, which prints the ACB estimated probability of intervention. Notice that the ACB assigns a probability for intervention greater than 0.50 on many days. And, notice that these spikes in probability are centered over intervention clusters. Even interventions the ACB fails to predict correspond to spikes in probability centered over these interventions. It is just that these spikes were not 0.50 or greater, which would then trigger a prediction. Overall, Figures 3.3 and 3.4 offer strong evidence in favor of the ACB.

5.2 Model Selection

To formally test the ACH versus the ACB, we conduct a Rivers and Vuong (2002) test, which modifies the Vuong (1989) test of non-nested likelihoods for time series data. Ideally, we would like to conduct a likelihood ratio test between the ACH and the ACB, as we can between the ACB and probit. However, this is not possible as one model does not nest the other. Fortunately, the Rivers and Vuong (2002) test allows us to do conduct such a test. The null hypothesis of the test is,

$$H_0 \;\; E_0\left[\mathcal{L}_t^{ACH} - \mathcal{L}_t^{ACB}\right] = 0,$$

which states that the two models are equally close to the true specification. Rivers and Vuong (2002) show that the test statistic is distributed Normal(0,1). Thus, if the statistic is statistically less than zero, the ACH is preferred. If the statistic is statistically greater than zero, the ACB is preferred. If the statistic is not statistically different from zero, the test cannot distinguish between the two models, given the data.

The Rivers and Vuong statistic (RV) is reported at the bottom of the tables listing the ACB results for each central bank. The probit is rejected in favor of the ACH at the 5%

level of significance or lower for the Bundesbank and full-sample Japan, and the ACH is rejected in favor of the ACB at a p-value of 0.0000 for all central banks. However, much like the SBC and *pseudo* R^2, the RV cannot reject the probit in favor of the ACH for the Federal Reserve. In fact, the sign of the RV favors the probit in this case.

Giacomini and Rossi (2007) point out that the Rivers and Vuong (RV, 2002) test selects the model based on *average* performance. As a result, in unstable environments, researchers may erroneously select a model based on average performance, ignoring the fact that the selection statistic may be reversed over a portion of the sample. To check if that is the case here, we compute Giacomini and Rossi's (2007) in-sample "fluctuation test". The fluctuation test computes the "fluctuation statistic", $F_{t,m}$, (which is based on the Kullback-Leibler Information Criterion, or "KLIC") over a moving window of size m:

$$F_{t,m} = \widehat{\sigma}^{-1} m^{-1} \sum_{j=t-m/2+1}^{t+m/2} \left(\mathcal{L}_j^{ACH} - \mathcal{L}_j^{ACB} \right), \; t = m/2+1, ..., T - m/2 \tag{14}$$

and plots $F_{t,m}$ along with critical values derived by Giacomini and Rossi for windows ranging from 0.1 to 0.9 of the total sample size.[26] If $F_{t,m}$ crosses the upper critical value, the ACH is rejected in favor of the ACB. If $F_{t,m}$ crosses the lower critical value, the ACB is rejected in favor of the ACH. If $F_{t,m}$ is in the middle of the two critical values, neither model is rejected. The motivation for plotting this statistic is to check whether or not the conclusion reached by the RV statistic is reversed over any of the windows.

Figure 3.5 illustrates the result of the fluctuation test over a moving window of 0.5 of the sample along with the 5% critical values (-2.779, 2.779).[27] Figure 3.5(a) plots the fluctuation statistic for the ACH versus the probit for the Federal Reserve. The result is consistent with the overall RV statistic. The probit is slightly preferred, but the ACH is never rejected in favor of the probit. However, the result of the fluctuation test for the ACH versus the probit for the other two central banks are startling. Even though the RV statistic rejects the probit in favor of the ACH for both the Bundesbank and Bank of Japan, the fluctuation test never rejects the probit in favor of the ACH. One reason for this is the RV statistic is distributed $Normal(0, 1)$, thus making the critical values (-1.645, 1.645) much smaller than those for the fluctuation test. More importantly, however, $F_{t,m}$ only dips below zero at the very beginning of the sample and during the mid 1990s for Japan (Figure 3.5(c)), and at the beginning of the sample for the Bundesbank. For the remainder of the sample, $F_{t,m}$ is slightly above zero for both. Thus, Giacomini and Rossi's (2007) concern that researchers may mistakenly select the wrong model based on average performance applies to the ACH.[28] However, this is not a concern for the ACB. As illustrated by Figure 3.5(b), the ACH is consistently rejected in favor of the ACB until the end of the sample, when intervention activity trails off (see Figure 3.1). The fluctuation statistic for the test of the ACH versus the ACB for the other two central banks is largely consistent with this result.

5.3 Summary

The result that the probit is preferred to the ACH for the Federal Reserve deserves attention, as the ACH is designed to be used with clustered data while the probit is not. Why is this the case? The answer is the functional form implied by the ACH and the significance of the lagged duration. Recall from equation (5) that the ACH places the functional form assumption on the lagged duration in that it assumes the probability of intervention is equal to the reciprocal of the lagged duration Also, recall from equation (1) that the expected duration is a decaying lag of past durations. Notice in Table 3.4 that the lagged duration is very insignificant for the Federal Reserve (p-value 0.7973) in the probit. Thus for the Federal Reserve, the ACH is using a very insignificant variable to impose the ACH functional form. Thus, it is no surprise that the probit, which does not make such an assumption, does better than the ACH for the Federal Reserve. Additional evidence for this claim is that for the Bundesbank and 1st and 2nd subsamples of the Bank of Japan, the lagged duration enters into the probit model significantly at least at the 10% level (for the full Japanese sample, p-value on the lagged duration is 0.1645). Thus, the functional form assumption made by the ACH for these central banks is not as severe and hence the ACH outperforms the probit. However, it is important to stress that the ACH is only able to outperform the probit *globally*, not *locally*.[29]

Finally, note from the tables that when we include the lagged duration in a dynamic ACB specification, the significance of it disappears. For the Bundesbank, the p-value on the lagged duration increases from 0.0264 in the probit to 0.2077 in the ACB(0,1,3). For the 1st subsample for Japan, the p-value of the lagged duration increases from 0.0105 in the probit to 0.7354 in the ACB(0,1,2) and for the 2nd subsample, the lagged duration is increased from 0.101 in the probit to 0.5073 in the ACB(0,1,2). Finally, for the full Japanese sample, the p-value of the lagged duration is increased from 0.1645 in the probit to 0.9815 in the ACB(0,1,3). Thus, the time dynamics of the clustered data are better captured through past response probabilities and past events, rather than past durations.

6 Conclusion

This chapter focused on two simultaneous goals. First, which binary model best captures the time dynamics present in "clustered" data such as data for sterilized central bank interventions in the foreign exchange market? Second, what motivations do central banks follow in deciding whether or not to intervene? We found persuasive evidence that the autoregressive conditional binomial model (ACB) outperformed the autoregressive conditional hazard (ACH) model. The ACB was preferred by each goodness-of-fit measure examined; the Schwarz Bayesian Criterion, the *pseudo* R^2, and the percentage of interventions correctly predicted. The Rivers and Vuong (2002) test of non-nested likelihoods rejected the ACH in favor of the ACB for all central banks. And, when the Rivers and Vuong test rejected the probit in favor of the ACH, the fluctuation test of Giacomini and Rossi (2007) found that this result was not stable over the sample. However, the rejection of the ACH in favor of the ACB was stable over the sample. These results are not only important for this paper's application, but for other applications that examine binary data with similar properties. That is, rather than estimating the ACH, or another offshoot of Engle and Russell's (1998) autoregressive conditional duration model, the dynamics can be captured using a dynamic binary model that nests a standard probit model. As we showed, the ACB model does a superior job capturing the time dynamics.

Using the ACB to examine the motivations for central banks intervention, we found that the Federal Reserve did not intervene in response to a deviation of the exchange rate from fundamentals. We found evidence that the Federal Reserve preferred to intervene when the market was calmer, and found that the spread between the 6-month Treasury Bill and Federal Funds rate contains predictive power for Federal Reserve intervention, suggesting a link between intervention and monetary policy decisions. Both results are novel. As far as we know, this is the first time a negative relationship between intervention and volatility has been shown using daily data, as well as the first time a link between intervention and the spread has been shown. We found that the Bundesbank intervened in response to the exchange rate deviating from the one implied by fundamentals and, like the Federal Reserve, that the Bundesbank intervened when the market was calmer. We found that the Bank of Japan was leaning *against* the wind during the time period before Sakakibara, whereas it leaned *with* the wind during Sakakibara. We also found little evidence for the Bank of Japan intervening in response to excess market volatility, a previously unexamined motivation.

Overall, the form of the time dynamics assumed in a binary model not only matters for global and local model performance, but also for the sign and significance of exogenous variables. By assuming a different form of time dynamics, we were able to not only increase model performance, but find new and novel results using daily intervention data. Thus, the form of time dynamics assumed in a binary model is important not only for this application, but future applications as well.

Notes

[1]An intervention is sterilized if it is offset by a corresponding change in the domestic monetary base, so that the intervention will have no net effect on the domestic money supply.

[2]See Sarno and Taylor (2001) for a thorough overview of the diverse opinions on this subject.

[3]In Japan, intervention is under the jurisdiction of the Ministry of Finance. Once intervention orders are given, they are carried out by the Bank of Japan. See Ito (2002).

[4]A seperate question is whether or not intervention is successful in altering the exchange rate. Although an interesting question, given the first paragraph of the introduction, it is outside of the scope of this chapter. Rather, we focus on why central banks intervene and how to control for the clustering present in the data.

[5]The authors are grateful to Richard Baillie for providing the data.

[6]See point 18 of the official G-5 Plaza announcement included in Funabashi (1989). Note that rather than using the term "depreciate", the G-5 uses the phrase "appreciate the main non-dollar currencies against the dollar".

[7]The Deutsche mark had fallen to 1.8250 against the dollar from a pre-Plaza level of 2.85 and the Yen had fallen to 153.50 against the dollar from a pre-Plaza level of 240. However, as Sarno and Taylor (2001) point out, the dollar was depreciating prior to the Plaza agreement.

[8]See Lawson's interview with the New York Times quoted in Funabashi (1989).

[9]The graph for the Bundesbank is very similar. Available upon request.

[10]This data is publicly available on the Japanese Ministry of Finance web site at http://www.mof.go.jp/english/e1c021.htm

[11]Sakakibara (2000) quoted in Ito (2002)

[12]We also follow Hamilton and Jorda (2002) in dropping the constant ω from equation (1) and instead include a constant in the denominator of the hazard in (5).

[13]Following Hamilton and Jorda (2002), we ensure that (5) is continually differentiable by replacing the denominator with a smoothing function defined as:

$$\lambda(\upsilon) = \left\{ \begin{array}{ccc} 1.0001 & if & \upsilon \leq 1 \\ 1.001 + \frac{2*0.1(\upsilon-1)^2}{0.1^2+(\upsilon-1)^2} & if & 1 < \upsilon \leq 1+0.1 \\ 0.0001 + \upsilon & if & \upsilon \geq 1+0.1 \end{array} \right\}$$

where υ is the denominator in (5) and $\lambda(\upsilon)$ is the denominator actually used in the estimation.

[14]Note that the only difference between this and the ACH is the ACH contains an infinite sum of decaying lags of the duration.

[15]See point 18 of the official G-5 Plaza Agreement announcement.

[16]We cannot reject the null hypothesis that $(s_{t-1} - s^*_{t-1})$ has a unit root (t-statistic: -

2.02). This result is robust to the inclusion of a time trend and to the inclusion of ten lags of the difference of the series in an augmented Dickey-Fuller test. Thus, we replace $(s_{t-1} - s^{*}_{t-1})$ with the first difference of it in the **z** vector of (5) for the Federal Reserve and Bundesbank. This is consistent with Meese and Singleton (1982) and Meese and Rogoff (1983) in that exchange rates appear to be I(1).

[17]That is, monetary policy is equivalent to unsterilized intervention.

[18]Daily data on all interest rates in the paper were downloaded from the Federal Reserve Bank of St. Louis FRED database, available at http://research.stlouisfed.org/fred2/

[19]Dollar/yen exchange rate data is taken from the FRED data base. This exchange rate data is the spot rate at 12:00P.M. in the New York market. This is advantageous because when it is 12:00P.M. in New York City, it is 2:00A.M. on the next day in Japan. Assuming that the Japanese are not intervening at 2:00A.M. we can believe that the ¥/$ are not being affected by Japanese intervention for that particular day.

[20]In all cases, the order of the ACB model was selected by comparing the selected model with a higher order model via a likelihood ratio test.

[21]In section 6, we argue that the ACB results should be preferred for both the Federal Reserve and Bundesbank.

[22]However, notice that $\alpha + \beta > 1$, which violates the stationarity condition given in section 4.1. This is obviously a disadvantage of the ACH model. We constrain β to ensure stationarity and reestimate the ACH model and obtain nearly identical results.

[23]However, like for the Bundesbank, the stationarity condition is violated for the Bank of Japan. And, like for the Bundesbank, the estimates are not dramatically different when β is constrained to ensure stationarity.

[24]Since, at most, 15% of the observations for a central bank contain an intervention, a model could have a PCP of 85% or greater simply by predicting 0 for each observation. Thus, to prevent the PCP from being so upwardly biased, we restrict it to predicting only interventions.

[25]Technically, the probit did assign a probability of intervention of 0.83 on 1/24/1991. However, no intervention took place on that day.

[26]$\widehat{\sigma}$ is a HAC estimator of the asymptotic variance given by Giacomini and Rossi (2007) and Rivers and Vuong (2002)

[27]To conserve space, we only plot the fluctuation statistic for the ACH versus probit and ACB models for the Federal Reserve, and for the ACH versus the probit model for the Bank of Japan. For the remainder of the specifications, we report the percentage of times the fluctuation statistic is above, below, and in the middle of the critical values in the tables reporting the probit and ACB results.

[28]In fact, setting the size of the moving window equal to the 1.0, $F^{IS}_{t,m}$ becomes the RV statistic, i.e., the "global ΔKLIC".

[29]One might wonder if the smoothing function in footnote 13 plays a role. To check this, we remove the smoothing function from the ACH. Specification (2) for the Federal Reserve cannot converge without it, but Specification (3) can. The estimated coefficients are generally robust between the two. And for full-sample Japan, the ACH cannot converge without the smoothing function. However, the sign and significance of the coefficients are robust between the ACH, probit, and ACB. Thus, although by no means conclusive, we find evidence that the smoothing funtion does not present a problem.

Table 3.1: Summary Statistics for Federal Reserve and Bundesbank Intervention

	Federal Reserve	Bundesbank
number of observations	1387	1461
number of interventions	173	210
number of dollar buys	65	55
number of dollar sells	108	155
largest dollar buy	\$395 million	\$567 million
largest dollar sell	\$740 million	\$887.7 million
smallest dollar buy	\$15 million	\$11.7 million
smallest dollar sell	\$25 million	\$2 million
weeks with 1 intervention	23	28
weeks with 2 interventions	27	31
weeks with 3 interventions	18	18
weeks with 4 interventions	8	9
weeks with 5 interventions	2	6
weeks with 0 interventions	222	225
number of dollar buys followed by dollar buys	60	50
number of dollar buys followed by dollar sells	4	4
number of dollar sells followed by dollar buys	4	4
number of dollar sells followed by dollar sells	104	151

Table 3.2: Summary Statistics for Bank of Japan Intervention

	full sample	1st subsample	2nd subsample
number of observations	2538	1038	1500
number of interventions	200	165	35
number of yen buys	32	26	6
number of yen sells	168	139	29
largest yen buy	¥2620.1 billion	¥76.9 billion	¥2620.1 billion
largest yen sell	¥1405.9 billion	¥338.8 billion	¥1405.9 billion
smallest yen buy	¥3.2 billion	¥3.2 billion	¥76.4 billion
smallest yen sell	¥5.1 billion	¥5.1 billion	¥43 billion
weeks with 1 intervention	44	23	16
weeks with 2 interventions	18	14	8
weeks with 3 interventions	15	14	1
weeks with 4 interventions	10	9	0
weeks with 5 interventions	7	7	0
weeks with 0 interventions	414	141	275
number of yen buys followed by yen buys	30	25	5
number of yen buys followed by yen sells	1	1	1
number of yen sells followed by yen buys	2	1	1
number of yen sells followed by yen sells	166	137	27

Table 3.3: ACH(1,1) Estimation Results for Federal Reserve and Bundesbank Intervention

parameter	variable	Federal Reserve (1)	Federal Reserve (2)	Bundesbank
α	$u_{N(t)-1}$	0.171***	0.173***	0.259**
		(0.0617)	(0.0615)	(0.115)
β	$\psi_{N(t)-1}$	0.511***	0.563***	0.800***
		(0.0949)	(0.0898)	(0.0745)
ω	constant	6.351***	6.11***	0.540***
		(0.831)	(0.741)	(0.438)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	0.0167	———	-0.00326
		(0.0199)		(0.00643)
γ_2	$abs(spread)_{t-1}$	-1.18***	-1.09***	———
		(0.321)	(0.296)	
γ_3	$\Delta\left(s_{t-1} - s_{t-1}^*\right)$	-140.15*	-99.48**	-10.83
		(72.06)	(47.48)	(28.16)
$\bar{\psi}$	expected duration	4.452	4.701	13.192
$\bar{h}$	average hazard	0.0990	0.0984	0.0728
log lik		-501.97	-502.31	-544.10
SBC		-523.67	-520.40	-562.32
$Pseudo\ R^2$		0.0381	0.0374	0.0954
PCP		0.000%	0.000%	0.7%

Notes:
Standard errors are in parentheses. * denotes statistical significance at the 10% level, while ** and *** denote it at the 5% and 1% level respectively. Only one specification reported for each sample unless significance of explanatory variables changed when insignificant variables are dropped and the model reestimated.

Table 3.4: ACB Estimation Results for Federal Reserve Intervention

parameter	variable	probit	ACB(0,1,2) (1)	(2)	(3)
ω	constant	-1.55*	-0.318*	-0.357***	-0.381***
		(0.0918)	(0.0727)	(0.0877)	(0.0910)
ρ	$G^{-1}(h_{t-1})$	——	0.0820**	0.0832**	0.0811*
			(0.0421)	(0.0408)	(0.0441)
δ_1	x_{t-1}	——	1.20***	1.16***	1.17***
			(0.123)	(0.124)	(0.124)
δ_2	x_{t-2}	——	-0.664***	-0.691***	-0.659***
			(0.165)	(0.159)	(0.162)
γ_1	$\left(\sigma_{t-1}^2 - \sigma^2\right)$	-0.00195	——	-0.00088**	-0.00082**
		(0.0015)		(0.00038)	(0.00041)
γ_2	$abs\,(spread)_{t-1}$	0.593*	——	0.0852**	0.0839**
		(0.100)		(0.0342)	(0.0351)
γ_3	$\Delta\left(s_{t-1} - s_{t-1}^*\right)$	4.21	——	5.52	——
		(5.80)		(3.59)	
γ_4	$u_{N(t-1)}$	-0.00051	——	0.00063	——
		(0.0020)		(0.00040)	
log lik		-500.84	-377.29	-368.81	-370.87
SBC		-518.92	-391.75	-397.75	-392.57
Pseudo R^2		0.0403	0.288	0.293	0.289
PCP		0.000%	45.2%	49.2%	42.4%
RV		0.165	6.63	7.16	6.93
p-value		0.4345	0.0000	0.0000	0.0000
Fluctuation	% above	0%	82.7%	83.0%	82.7%
	% between	100%	17.3%	17.0%	17.3%
	% below	0%	0%	0%	0%

Notes:
Standard errors are in parentheses. * denotes statistical significance at the 10% level, while ** and *** denote it at the 5% and 1% level respectively.

Table 3.5: ACB Estimation Results for Bundesbank Intervention

parameter	variable	probit	ACB(0,1,3) (1)	(2)	(3)
ω	constant	-1.06***	-0.16***	-0.0575*	-0.0423
		(0.0405)	(0.0770)	(0.0350)	(0.0275)
ρ	$G^{-1}(h_{t-1})$	——	0.91***	0.968***	0.975***
			(0.0445)	(0.0187)	(0.0150)
δ_1	x_{t-1}	——	1.11***	1.09***	1.11***
			(0.121)	(0.121)	(0.121)
δ_2	x_{t-2}	——	-0.47***	-0.541***	-0.550***
			(0.194)	(0.197)	(0.198)
δ_3	x_{t-3}	——	-0.35***	-0.453***	-0.486***
			(0.163)	(0.130)	(0.125)
γ_1	$\left(\sigma^2_{t-1} - \sigma^2\right)$	-0.00154	——	-0.00031***	-0.00029***
		(0.00131)		(0.000122)	(9.23e-005)
γ_2	$\Delta\left(s_{t-1} - s^*_{t-1}\right)$	0.504	——	3.99***	3.84***
		(3.20)		(1.51)	(1.37)
$\gamma 3$	$u_{N(t-1)}$	-0.0046**	——	0.000177	——
		(0.00209)		(0.000141)	
log lik		-597.77	-411.80	-405.09	-406.11
SBC		-608.70	-430.02	-434.23	-431.61
Pseudo R^2		0.00617	0.315	0.327	0.325
PCP		0.000%	45.2%	42.9%	42.4%
RV		-2.32	5.94	6.10	6.14
p-value		0.0102	0.0000	0.0000	0.0000
Fluctuation	% above	0%	66.7%	66.7%	66.7%
	% between	100%	33.3%	33.3%	33.3%
	% below	0%	0%	0%	0%

Notes:
Standard errors are in parentheses. * denotes statistical significance at the 10% level, while ** and *** denote it at the 5% and 1% level respectively.

Table 3.6: ACH(1,1) Estimation Results for Bank of Japan Intervention

parameter	variable	full sample	1st subsample (1)	(2)	2nd subsample
α	$u_{N(t)-1}$	0.376***	0.458*	0.486**	1.02e-010
		(0.132)	(0.255)	(0.212)	(0.0994)
β	$\psi_{N(t)-1}$	0.707***	3.98e-012	0.170	0.00#
		(0.0532)	(0.137)	(0.192)	
ω	constant	2.44***	4.38***	4.06***	49.12***
		(0.884)	(0.654)	(0.870)	(12.96)
γ_1	$(\sigma^2_{t-1} - \sigma^2)$	-0.00515	-0.0285	——	0.362***
		(0.0255)	(0.0227)		(0.0405)
γ_2	$(s_{t-1} - s_{t-2})$	86.54***	81.97*	112.32***	-2093.03***
		(27.80)	(42.77)	(25.27)	(711.57)
$\overline{\psi}$		21.428	4.812	6.145	2.15e-009
$\overline{h}$		0.0419	0.0107	0.0912	0.0191
log lik		-647.63	-437.07	-437.91	-155.26
SBC		-667.23	-454.43	-451.80	-173.54
Pseudo R^2		0.0749	0.0385	0.0367	0.0653
PCP		0.04%	0.1%	0.1%	0.1%

Notes:
Standard errors are in parentheses. * denotes statistical significance at the 10% level, while ** and *** denote it at the 5% and 1% level respectively. #: β constrained to 0.00 to ensure convergence. Only one specification reported for each sample unless significance of explanatory variables changed when insignificant variables are dropped and the model reestimated.

Table 3.7: ACB Estimation Results for Bank of Japan (full sample)

parameter	variable	probit	ACB(0,1,3) (1)	(2)	(3)
ω	constant	-1.38***	-0.217***	-0.304***	-0.312***
		(0.0399)	(0.0910)	(0.0696)	(0.0728)
ρ	$G^{-1}(h_{t-1})$	——	0.890***	0.846***	0.843***
			(0.0466)	(0.0352)	(0.0366)
δ_1	x_{t-1}	——	1.24***	1.12***	1.14***
			(0.121)	(0.125)	(0.124)
δ_2	x_{t-2}	——	-0.414**	-0.323*	-0.327*
			(0.195)	(0.196)	(0.195)
δ_3	x_{t-3}	——	-0.438***	-0.320**	-0.318**
			(0.171)	(0.146)	(0.147)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	-0.00293	——	-0.000801*	——
		(0.00192)		(0.000443)	
γ_2	$(s_{t-1} - s_{t-2})$	-9.39**	——	-16.32***	-15.21***
		(4.76)		(3.60)	(3.46)
γ_3	$u_{N(t-1)}$	-0.00168	——	6.89e-005	——
		(0.00121)		(0.00297)	
log lik		-694.61	-463.05	-448.80	-451.04
SBC		-710.29	-483.64	-480.15	-474.56
Pseudo R^2		0.00780	0.339	0.359	0.356
PCP		0.000%	41.5%	41.0%	41.5%
RV		-2.00	6.73	6.49	6.51
p-value		0.0228	0.0000	0.0000	0.0000
Fluctuation	% above	0%	65.9%	66.9%	66.5%
	% between	100%	34.1%	33.1%	33.5%
	% below	0%	0%	0%	0%

Notes:
Standard errors are in parentheses. * denotes statistical significance at the 10% level, while ** and *** denote it at the 5% and 1% level respectively.

Table 3.8: ACB Estimation Results for Bank of Japan Intervention (1st subsample)

parameter	variable	probit	ACB(0,1,2) (1)	(2)	(3)
ω	constant	-0.872***	-0.411***	-0.398***	-0.399***
		(0.0554)	(0.104)	(0.0895)	(0.0876)
ρ	$G^{-1}(h_{t-1})$	——	0.757***	0.770***	0.776***
			(0.0636)	(0.0522)	(0.0491)
δ_1	x_{t-1}	——	1.22***	1.09***	1.09***
			(0.137)	(0.143)	(0.142)
δ_2	x_{t-2}	——	-0.540**	-4.98***	-0.497***
			(0.213)	(0.195)	(0.192)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	0.0177***	——	0.000971	——
		(0.00411)		(0.00136)	
γ_2	$(s_{t-1} - s_{t-2})$	-24.14***	——	-34.59***	-34.37***
		(7.05)		(6.32)	(6.32)
γ_3	$u_{N(t-1)}$	-0.00672***	——	-0.000292	——
		(0.00262)		(0.000865)	
log lik		-435.01	-308.61	-290.44	-290.77
SBC		-448.90	-322.50	-314.75	-308.13
Pseudo R^2		0.0431	0.321	0.361	0.360
PCP		0.6%	54.5%	57.6%	59.4%
RV		0.3531	6.74	6.84	6.84
p-value		0.3620	0.0000	0.0000	0.0000

Notes:
Standard errors are in parentheses. * denotes statistical significance at the 10% level, while ** and *** denote it at the 5% and 1% level respectively.

Table 3.9: ACB Estimation Results for the Bank of Japan (2nd subsample)

parameter	variable	probit	ACB(0,1,2) (1)	(2)	(3)
ω	constant	-2.07***	-2.55***	-3.14***	-3.12***
		(0.0844)	(0.526)	(0.292)	(0.280)
ρ	$G^{-1}(h_{t-1})$	———	-0.188	-0.398***	-0.415***
			(0.242)	(0.116)	(0.111)
δ_1	x_{t-1}	———	1.13***	1.30***	1.34***
			(0.265)	(0.280)	(0.273)
δ_2	x_{t-2}	———	1.35***	1.49***	1.48***
			(0.393)	(0.285)	(0.285)
γ_1	$(\sigma_{t-1}^2 - \sigma^2)$	0.000145	———	0.00201	———
		(0.00279)		(0.00412)	
γ_2	$(s_{t-1} - s_{t-2})$	16.60***	———	26.82***	28.47***
		(7.80)		(7.90)	(7.78)
γ_3	$u_{N(t-1)}$	0.00242*	———	0.00132	———
		(0.00148)		(0.00199)	
log lik		-162.03	-145.26	-138.62	-139.08
SBC		-176.65	-159.89	-164.22	-157.36
Pseudo R^2		0.0246	0.126	0.165	0.163
PCP		0.000%	14.3%	11.4%	11.4%
RV		-1.48	0.814	1.60	1.56
p-value		0.0694	0.2078	0.0548	0.0594

Notes:
Standard errors are in parentheses. * denotes statistical significance at the 10% level, while ** and *** denote it at the 5% and 1% level respectively.

Figure 3.1: Number of Interventions Per Week for the Federal Reserve

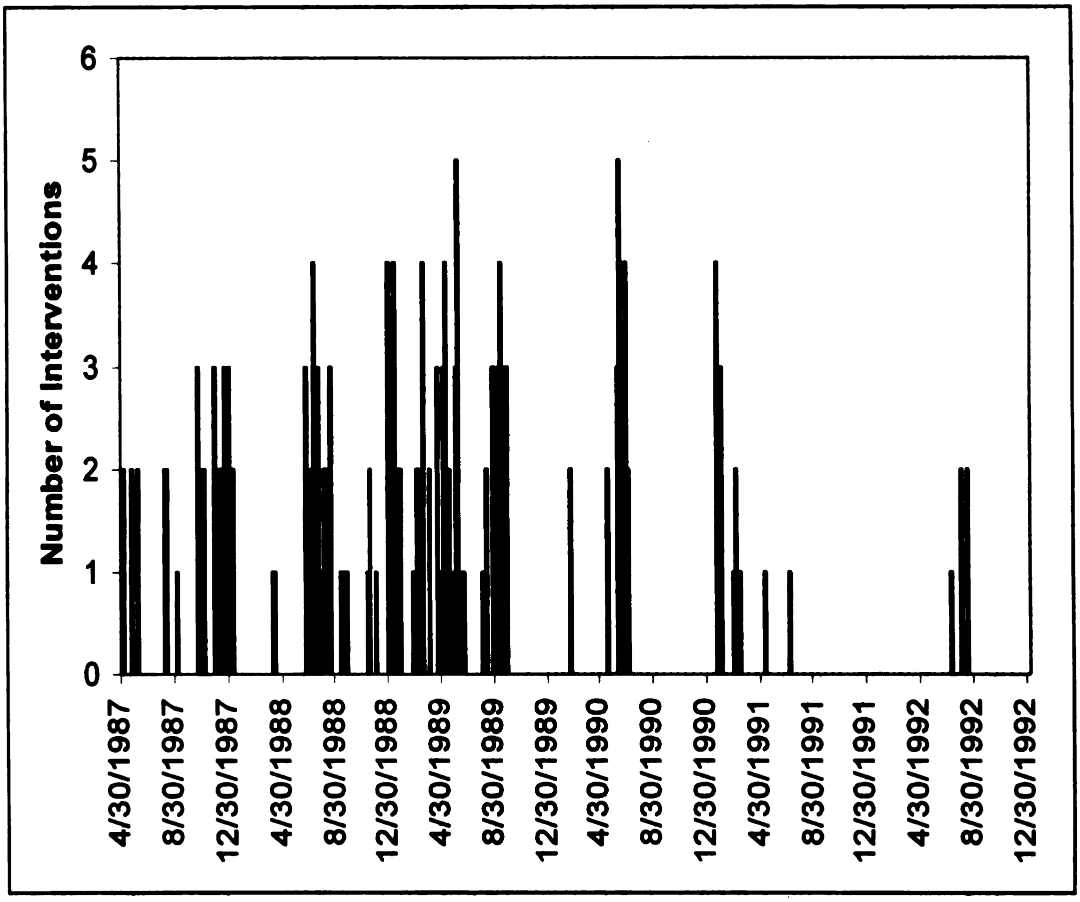


Figure 3.2: Number of Interventions Per Week for the Bank of Japan

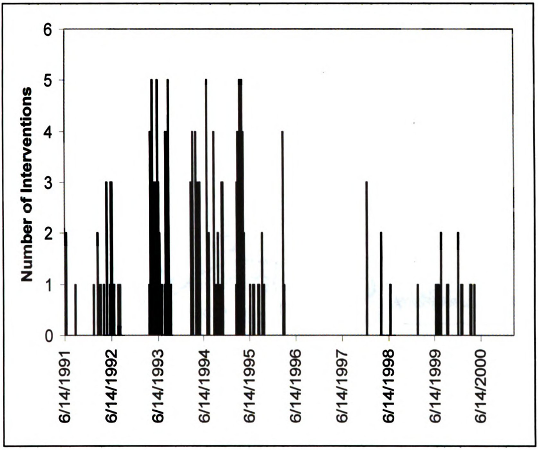
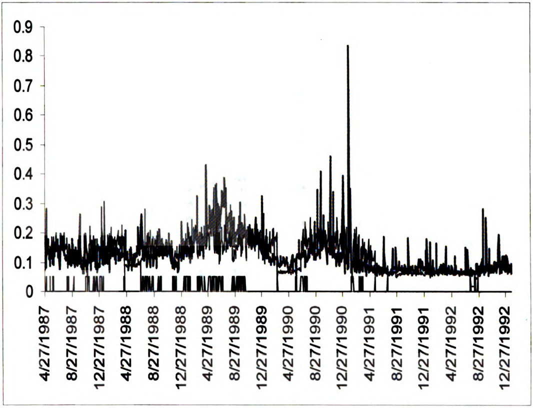
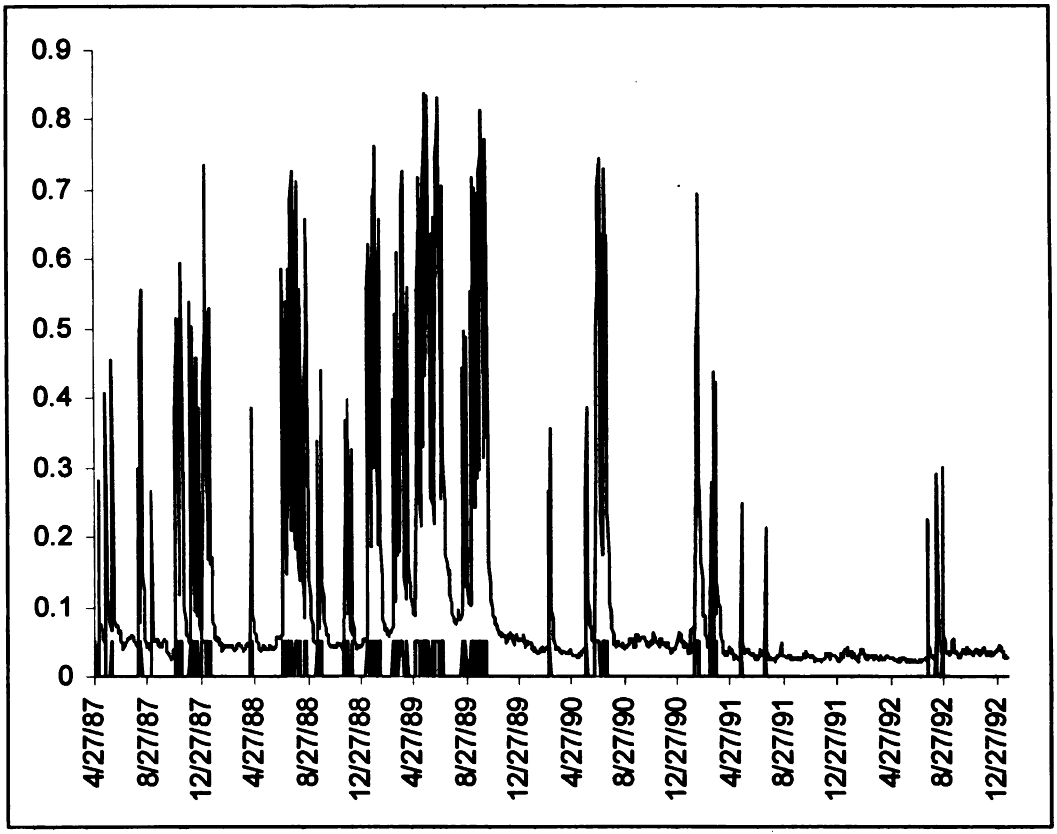


Figure 3.3: ACH and Probit Estimated Probability of Intervention for the Federal Reserve



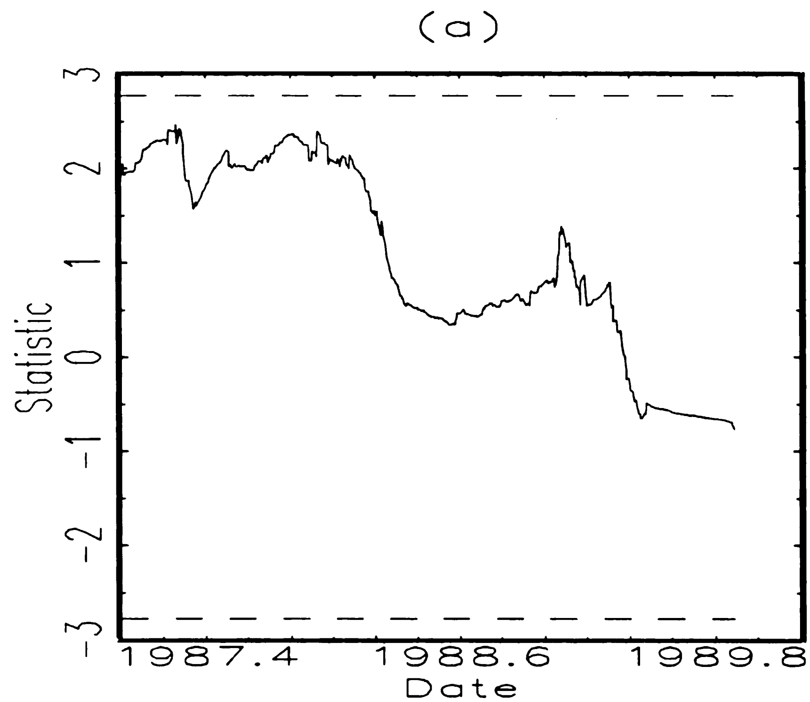
Notes:
Black line corresponds to the ACH. Grey line corresponds to the Probit.
Black marks along x-axis indicate an intervention took place on that date.

Figure 3.4: ACB(0,1,2) Estimated Probability of Intervention for the Federal Reserve



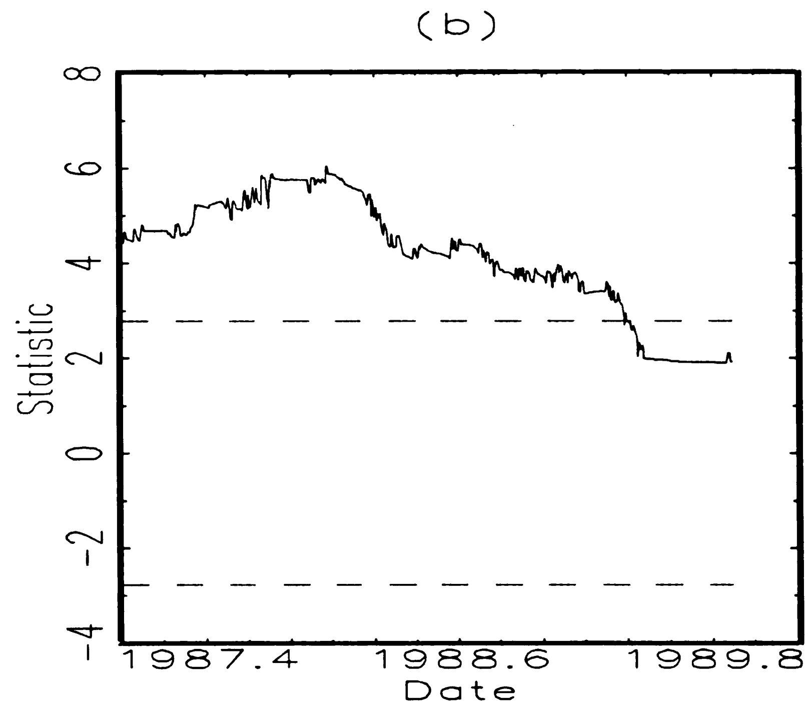
Notes:
Black marks along x-axis indicate an intervention took place on that date.

Figure 3.5: Fluctuation Test



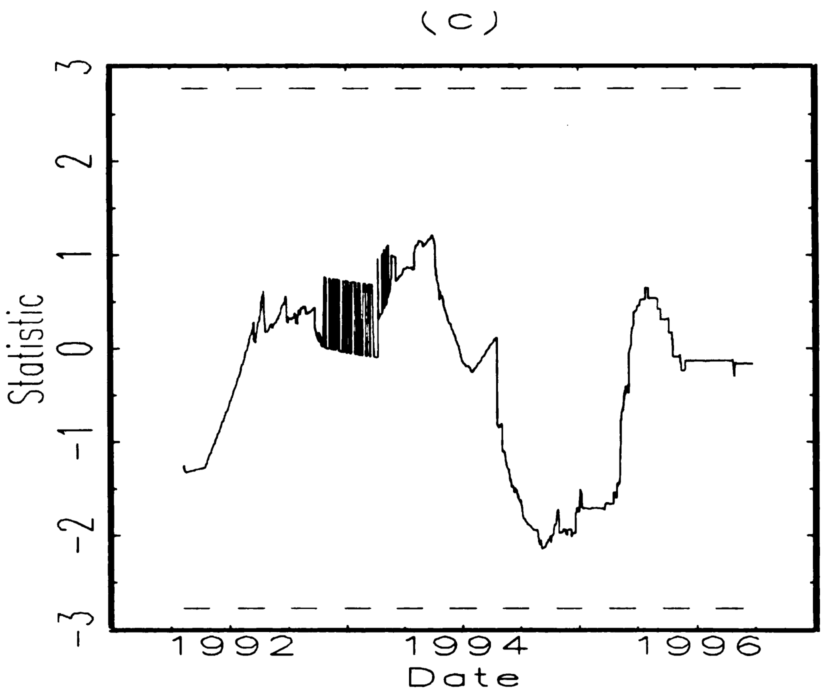
Notes:
Results of the fluctuation test for (a)ACH vs. probit for the Federal Reserve, (b)ACH vs. ACB (specification 2) for the Federal Reserve, and (c)ACH vs. probit for Japan. The dates correspond to the *first* date of the window.

Figure 3.5 (continued)



Notes:
Results of the fluctuation test for (a)ACH vs. probit for the Federal Reserve, (b)ACH vs. ACB (specification 2) for the Federal Reserve, and (c)ACH vs. probit for Japan. The dates correspond to the *first* date of the window.

Figure 3.5 (continued)



Notes:
Results of the fluctuation test for (a)ACH vs. probit for the Federal Reserve, (b)ACH vs. ACB (specification 2) for the Federal Reserve, and (c)ACH vs. probit for Japan. The dates correspond to the *first* date of the window.

Appendix 1: Data

1 Data Sources

Our main data source is the Standard and Poor's Compustat North America, which provides data items on over 24,000 companies that have filed with the SEC. The Compustat data items provide information on firms' Balance Sheets, Statements of Cash Flows, Income statements, and other supplemental information. We removed all firms classified under the industry group Finance, Insurance, and Real Estate. Effectively, we deleted all firms whose DNUM variable (explained below) was in the interval [6000, 7000). For the annual sample, this left us with 20112 firms and 202897 credit flow observations, which means that the average firm stays in the database for about 10 years. For the quarterly sample, this left us with 18753 firms and 545181 credit flow observations implying an average stay of slightly above 7 years. The numbers for credit flow observations pertain to total credit; the numbers for short-term and long-term credit were almost identical, with the discrepancy being due to some observations missing for the short-term credit but not for the long-term and vice-versa.

The macroeconomic variables were downloaded from the FRED II database of the Federal Reserve Bank of St. Louis.

2 Variables

Short-Term Credit: Balance sheet annual (quarterly) data item 34 (45), "debt in current liabilities" (original source: Compustat).

Long-Term Credit: Balance sheet annual (quarterly) data item 9 (51), "total long-term debt" (original source: Compustat).

GDP: Quarterly GDP in billions of 2000 chained dollars, seasonally adjusted at annual rates (original source: U.S. Department of Commerce, Bureau of Economic Analysis).

Unemployment Rate: Original source: U.S. Department of Labor, Bureau of Labor Statistics, Series ID LNS14000000. Annual series were computed by taking the average across monthly values.

CPI: Consumer Price Index for all urban consumers (all items), index 1982-1984=100, seasonally adjusted (original source: U.S. Department of Labor, Bureau of Labor Statistics). Quarterly series were computed by taking the observation for the last month of the quarter.

Federal Funds Rate: Effective federal funds rate available from the Federal Reserve Board. Quarterly series were computed by taking the observation for the last month in the quarter.

GDP Implicit Price Deflator: Original source: Bureau of Economic Analysis.

3 Classification

Industry. There are two variables available in Compustat that identify an industry type. The variable NAICS provides the North American Industry Classification System (NAICS) codes, while the variable DNUM provides 4-digit industry codes based on the former Standard Industrial Classification (SIC) system. The NAICS variable contains a missing value for around 10% of the observations. Fortunately, the variable DNUM contains no missing values, and therefore was chosen to be used when separating firms into industry groups and subgroups. The coding for DNUM is almost identical to the SIC classification, and can be safely treated as such for the purposes of this paper.

Size and Location. The subdivision among the census regions is based on the Compustat variable STATE, which identifies a state according to a firm's principal location. The subdivision into quartiles and deciles by size is based on the Compustat data item 12, Net Sales.

4 Remarks

Firm Entry. To separate firms entering Compustat between newly created and already existing we construct a ratio of the gross book value of capital to the net book value of capital. If this ratio is not larger than 1.2 for a given firm then this firm is assumed to be newly formed. The ratio is computed as $\frac{DataItem7}{DataItem7 - DataItem196}$, where data item 7 is total gross property, plant, and equipment, and data item 196 is accumulated depreciation, depletion, and amortization as provided by Compustat.

Firm Exit. When a firm exits the Compustat database its growth rate and total credit are counted only if the footnote item AFTNT 35 takes on values between 1 and 4 (exit due to acquisition or merger, bankruptcy, liquidation, or reverse acquisition). The firm is ignored for the exiting period if the reason code equals 5, 6, 9, or 10 (exit due to leveraged buyout, conversion to a private company, or other reasons).

Appendix 2: Results for All Lags

Table 4.1: Results for All Lags

	Pooled OLS Full Sample $\log\left(\frac{AP}{Assets}\right)$	Fixed Effects Full Sample $\log\left(\frac{AP}{Assets}\right)$	Pooled OLS Instrument Sample $\log\left(\frac{AP}{Assets}\right)$
Comovement	-0.118*** ooo	-0.098*** oo	-0.138* oo
	(0.0394) [0.0455]	(0.0329) [0.0384]	(0.0758) [0.0581]
lag1	-0.074*** oo	-0.065** oo	0.124*** ooo
	(0.0289) [0.0323]	(0.0268) [0.0291]	(0.0470) [0.0373]
lag2	0.063** oo	0.038	-0.096** ooo
	(0.0254) [0.0268]	(0.0234) [0.0259]	(0.0473) [0.0311]
lag3	0.196***	0.189*** ooo	0.014
	(0.0302) [0.0343]	(0.0277) [0.0309]	(0.0502) [0.0467]
lag4	-0.074**	-0.097*** ooo	0.090 o
	(0.0370) [0.0429]	(0.0327) [0.0367]	(0.0677) [0.0489]
log (book value of assets)	-0.005	-0.019	-0.008
	(0.0277) [0.0400]	(0.0203) [0.0264]	(0.0331) [0.0487]
lag1	-0.157*** ooo	-0.128*** ooo	-0.133*** ooo
	(0.0170) [0.0261]	(0.0125) [0.0157]	(0.0165) [0.0245]
lag2	0.001	0.002	0.006
	(0.0180) [0.0295]	(0.0123) [0.0169]	(0.0203) [0.0358]
lag3	0.047**	0.008	0.008
	(0.0188) [0.0310]	(0.0123) [0.0175]	(0.0188) [0.0239]
lag4	0.112*** ooo	0.032**	0.147*** ooo
	(0.0248) [0.0400]	(0.0136) [0.0214]	(0.0182) [0.0246]
Net Profit/Assets, if profit>0	-0.235*** ooo	-0.121*** oo	-0.369*** ooo
	(0.0495) [0.0821]	(0.0305) [0.0538]	(0.1004) [0.1383]
lag1	-0.303*** ooo	-0.153*** oo	-0.155*
	(0.0730) [0.0841]	(0.0429) [0.0621]	(0.0811) [0.1362]
lag2	-0.146**	-0.061*	-0.229*** oo
	(0.0606) [0.0925]	(0.0325) [0.0607]	(0.0716) [0.1118]
lag3	-0.155**	-0.059**	-0.290*** oo
	(0.0632) [0.0973]	(0.0297) [0.0511]	(0.0878) [0.1141]
lag4	-0.145**	-0.055*	-0.179**
	(0.0645) [0.0981]	(0.0303) [0.0593]	(0.0763) [0.1106]

Table 4.1 (continued)

	Pooled OLS Full Sample $\log\left(\frac{AP}{Assets}\right)$	Fixed Effects Full Sample $\log\left(\frac{AP}{Assets}\right)$	Pooled OLS Instrument Sample $\log\left(\frac{AP}{Assets}\right)$
Net Profit/Assets,	-0.420*** oo	-0.340*** ooo	-0.709*** ooo
if profit<0 & Δsales>0	(0.1213) [0.1692]	(0.0889) [0.1129]	(0.0913) [0.1264]
lag1	-0.263**	-0.245*** ooo	-0.476*** ooo
	(0.1087) [0.1678]	(0.0692) [0.0945]	(0.0693) [0.0874]
lag2	-0.321*** oo	-0.207*** oo	-0.414*** ooo
	(0.1111) [0.1520]	(0.0668) [0.1026]	(0.0782) [0.1035]
lag3	0.055	-0.027	0.006
	(0.1388) [0.1875]	(0.0505) [0.0931]	(0.0699) [0.1369]
lag4	-0.092	-0.066	-0.055
	(0.0843) [0.0977]	(0.0450) [0.0619]	(0.0775) [0.1406]
Net Profit/Assets,	-0.390*** oo	-0.284*** oo	-0.689*** ooo
if profit<0 & Δsales<0	(0.1074) [0.1688]	(0.0844) [0.1332]	(0.0888) [0.1393]
lag1	-0.256*** o	-0.179*** o	-0.488*** ooo
	(0.0887) [0.1391]	(0.0616) [0.0958]	(0.0686) [0.1205]
lag2	-0.248** o	-0.164*** oo	-0.334*** ooo
	(0.0969) [0.1392]	(0.0600) [0.0815]	(0.0651) [0.1173]
lag3	-0.261*** oo	-0.155*** ooo	-0.212*** oo
	(0.0707) [0.1072]	(0.0354) [0.0560]	(0.0685) [0.1004]
lag4	-0.397*** ooo	-0.220*** ooo	-0.455*** ooo
	(0.0641) [0.1133]	(0.0279) [0.0527]	(0.0624) [0.1137]
Δsales/Assets,	0.614*** ooo	0.419*** ooo	0.420
if positive, 0 otherwise	(0.1738) [0.2057]	(0.1207) [0.1397]	(0.3108) [0.4496]
lag1	0.622*** ooo	0.372*** ooo	0.627**
	(0.1647) [0.2242]	(0.1099) [0.1420]	(0.2802) [0.3867]
lag2	0.440*** oo	0.257*** oo	1.008*** ooo
	(0.1518) [0.2178]	(0.0697) [0.1068]	(0.0832) [0.1360]
lag3	0.304**	0.188**	0.893*** ooo
	(0.1295) [0.2686]	(0.0755) [0.1494]	(0.0786) [0.1150]
lag4	0.276***	0.192*** o	0.839*** ooo
	(0.0989) [0.1931]	(0.0636) [0.1090]	(0.0806) [0.1138]

Table 4.1 (continued)

	Pooled OLS Full Sample $\log\left(\frac{AP}{Assets}\right)$	Fixed Effects Full Sample $\log\left(\frac{AP}{Assets}\right)$	Pooled OLS Instrument Sample $\log\left(\frac{AP}{Assets}\right)$
Δsales/Assets,	0.103*	0.202*** ooo	0.154
if negative, 0 otherwise	(0.0623) [0.1283]	(0.0381) [0.0730]	(0.1054) [0.1493]
lag1	-0.024	0.090**	0.176**
	(0.0759) [0.1457]	(0.0364) [0.0710]	(0.0893) [0.1166]
lag2	-0.009	-0.009	0.001
	(0.1086) [0.1900]	(0.0526) [0.0932]	(0.1365) [0.1871]
lag3	-0.042	0.072	-0.039
	(0.0821) [0.1106]	(0.0449) [0.0565]	(0.1075) [0.1558]
lag4	-0.071	0.033	-0.155**
	(0.0592) [0.0858]	(0.0346) [0.0470]	(0.0679) [0.1093]
log (1+firm age)	-0.101**	0.117	-0.109
	(0.0505) [0.0709]	(0.1014) [0.1309]	(0.0781) [0.0914]
$[\log(1+\text{firm age})]^2$	0.016**	-0.013	0.016
	(0.0078) [0.0113]	(0.0217) [0.0278]	(0.0122) [0.0144]
(Current Assets-Cash)/Assets	1.741*** ooo	1.676*** ooo	1.804*** ooo
	(0.0705) [0.1098]	(0.0538) [0.0739]	(0.1192) [0.1732]
lag1	0.255*** ooo	0.200*** ooo	0.243*** ooo
	(0.0361) [0.0504]	(0.0312) [0.0431]	(0.0464) [0.0666]
lag2	0.191*** ooo	0.162*** ooo	0.145**
	(0.0531) [0.0587]	(0.0355) [0.0372]	(0.0699) [0.0959]
lag3	0.228*** ooo	0.145*** ooo	0.142*** oo
	(0.0395) [0.0595]	(0.0284) [0.0356]	(0.0490) [0.0670]
lag4	0.160*** o	0.120*** oo	0.181*** oo
	(0.0557) [0.0907]	(0.0357) [0.0501]	(0.0609) [0.0908]
Inventories / Assets	0.739*** ooo	0.762*** ooo	0.678*** ooo
	(0.0924) [0.1233]	(0.0743) [0.1026]	(0.1526) [0.2113]
lag1	-1.021*** ooo	-0.951*** ooo	-0.949*** ooo
	(0.0621) [0.0752]	(0.0534) [0.0738]	(0.0891) [0.1456]
lag2	-0.344*** ooo	-0.266*** ooo	-0.271*** oo
	(0.0774) [0.0955]	(0.0509) [0.0628]	(0.0817) [0.1077]
lag3	-0.344*** ooo	-0.157*** oo	-0.269*** ooo
	(0.0749) [0.1095]	(0.0461) [0.0621]	(0.0580) [0.0921]
lag4	-0.080	-0.087*	-0.178**
	(0.0683) [0.1037]	(0.0494) [0.0766]	(0.0846) [0.1200]

Table 4.1 (continued)

	Pooled OLS Full Sample $\log\left(\frac{AP}{Assets}\right)$	Fixed Effects Full Sample $\log\left(\frac{AP}{Assets}\right)$	Pooled OLS Instrument Sample $\log\left(\frac{AP}{Assets}\right)$
Ret.Earnings / Assets	-0.001*	-0.002***	-0.005***
	(0.0007) [0.0051]	(0.0004) [0.0043]	(0.0020) [0.0163]
lag1	0.002***	0.002***	-0.001
	(0.0007) [0.0044]	(0.0004) [0.0022]	(0.0010) [0.0047]
lag2	0.0002	0.001**	-0.002
	(0.0011) [0.0048]	(0.0006) [0.0027]	(0.0014) [0.0106]
lag3	-0.010***	-0.003**	-0.002**
	(0.0036) [0.0069]	(0.0012) [0.0032]	(0.0010) [0.0034]
lag4	-0.004*	0.0005	-0.001
	(0.0022) [0.0071]	(0.0014) [0.0030]	(0.0013) [0.0063]
T-Bill	0.011*** ooo	0.012*** ooo	0.015*** ooo
	(0.0010) [0.0017]	(0.0009) [0.0016]	(0.0016) [0.0024]
lag1	-0.003**	-0.002**	-0.002
	(0.0013) [0.0019]	(0.0012) [0.0016]	(0.0021) [0.0029]
lag2	0.002**	0.002* o	0.002
	(0.0011) [0.0015]	(0.0010) [0.0012]	(0.0017) [0.0025]
lag3	0.002**	0.001	0.002
	(0.0012) [0.0018]	(0.0011) [0.0016]	(0.0018) [0.0025]
lag4	-0.002*	-0.004*** ooo	-0.005*** oo
	(0.0012) [0.0019]	(0.0010) [0.0014]	(0.0017) [0.0022]
4 Lags of Regressors Included	Yes	Yes	Yes
Year and Quarter Dummies	Yes	Yes	Yes
4-digit SIC Industry Dummies	Yes	No	Yes
R-squared	0.47	0.26	0.40
Obs	280512	280512	107965
Firms	9369	9369	3798

Table 4.1 (continued)

	Fixed Effects Instrument Sample $\log\left(\frac{AP}{Assets}\right)$	2 SLS Instrument Sample $\log\left(\frac{AP}{Assets}\right)$	FE-IV Instrument Sample $\log\left(\frac{AP}{Assets}\right)$
Comovement	-0.007	-0.930	-2.537
	(0.0663) [0.0606]	(6.5204) [30.50]	(5.6860) [86.69]
lag1	0.082* ᵒ	-0.956	-1.647
	(0.0439) [0.0474]	(6.6295) [28.48]	(5.5713) [132.7]
lag2	-0.093** ᵒᵒ	15.46	12.41
	(0.0440) [0.0420]	(10.324) [24.27]	(8.6969) [79.70]
lag3	0.017	-14.01*	-12.39*
	(0.0464) [0.0530]	(8.055) [43.41]	(6.5438) [111.0]
lag4	-0.024	2.457	4.593
	(0.0582) [0.0580]	(4.5331) [20.27]	(3.5672) [131.1]
log (book value of assets)	-0.021	-0.020	-0.027
	(0.0254) [0.0384]	(0.0350) [0.1313]	(0.0273) [0.2405]
lag1	-0.134*** ᵒᵒᵒ	-0.110***	-0.117***
	(0.0158) [0.0218]	(0.0277) [0.1095]	(0.0241) [0.4529]
lag2	0.002	0.006	0.001
	(0.0159) [0.0266]	(0.0240) [0.0809]	(0.0194) [0.6602]
lag3	0.002	-0.021	-0.019
	(0.0147) [0.0206]	(0.0283) [0.0611]	(0.0217) [0.0978]
lag4	0.037** ᵒ	0.163*** ᵒᵒᵒ	0.048***
	(0.0153) [0.0193]	(0.0215) [0.0578]	(0.0177) [0.3977]
Net Profit/Assets, if profit>0	-0.186*** ᵒ	-0.366***	-0.165**
	(0.0697) [0.1081]	(0.1052) [0.3302]	(0.0731) [0.7521]
lag1	-0.043	-0.177**	-0.049
	(0.0607) [0.0936]	(0.0893) [0.1792]	(0.0629) [0.9018]
lag2	-0.099**	-0.241***	-0.095**
	(0.0429) [0.0812]	(0.0771) [0.2782]	(0.0461) [1.421]
lag3	-0.148*** ᵒ	-0.296***	-0.141**
	(0.0543) [0.0763]	(0.0952) [0.2843]	(0.0577) [1.919]
lag4	-0.095*	-0.186**	-0.086*
	(0.0507) [0.0893]	(0.0774) [0.2029]	(0.0502) [0.8954]

Table 4.1 (continued)

	Fixed Effects Instrument Sample $\log\left(\frac{AP}{Assets}\right)$	2 SLS Instrument Sample $\log\left(\frac{AP}{Assets}\right)$	FE-IV Instrument Sample $\log\left(\frac{AP}{Assets}\right)$
Net Profit/Assets,	-0.526*** ooo	-0.726*** ooo	-0.536***
if profit<0 & Δsales>0	(0.0735) [0.1082]	(0.0953) [0.1518]	(0.0764) [0.4281]
lag1	-0.322*** ooo	-0.482*** ooo	-0.322***
	(0.0486) [0.0718]	(0.0712) [0.1284]	(0.0491) [1.028]
lag2	-0.245*** ooo	-0.402*** ooo	-0.234***
	(0.0458) [0.0756]	(0.0777) [0.1198]	(0.0460) [1.818]
lag3	-0.015	0.003	-0.018
	(0.0489) [0.1010]	(0.0710) [0.1487]	(0.0495) [1.426]
lag4	-0.026	-0.056	-0.026
	(0.0493) [0.0930]	(0.0799) [0.1519]	(0.0503) [0.7399]
Net Profit/Assets,	-0.563*** ooo	-0.696*** ooo	-0.568***
if profit<0 & Δsales<0	(0.0796) [0.1148]	(0.0923) [0.1353]	(0.0803) [0.5873]
lag1	-0.370*** ooo	-0.500*** ooo	-0.381***
	(0.0530) [0.0821]	(0.0711) [0.1791]	(0.0545) [0.9523]
lag2	-0.217*** ooo	-0.327*** o	-0.215***
	(0.0526) [0.0720]	(0.0683) [0.1734]	(0.0547) [0.6915]
lag3	-0.113** o	-0.199***	-0.106*
	(0.0515) [0.0685]	(0.0709) [0.1418]	(0.0542) [0.5747]
lag4	-0.236*** ooo	-0.451*** oo	-0.229***
	(0.0434) [0.0694]	(0.0647) [0.1966]	(0.0454) [0.3967]
Δsales/Assets,	0.292	0.427	0.295
if positive, 0 otherwise	(0.2103) [0.3068]	(0.3192) [0.4874]	(0.2146) [0.6860]
lag1	0.378**	0.624**	0.380**
	(0.1909) [0.2629]	(0.2809) [0.4590]	(0.1934) [1.574]
lag2	0.544*** ooo	0.971*** ooo	0.510***
	(0.0705) [0.1137]	(0.0911) [0.2800]	(0.0770) [1.176]
lag3	0.474*** ooo	0.916*** oo	0.491***
	(0.0661) [0.0892]	(0.0870) [0.3951]	(0.0761) [1.851]
lag4	0.485*** ooo	0.824*** ooo	0.466***
	(0.0444) [0.0694]	(0.0854) [0.2777]	(0.0505) [0.9167]

Table 4.1 (continued)

	Fixed Effects Instrument Sample $\log(\frac{AP}{Assets})$	2 SLS Instrument Sample $\log(\frac{AP}{Assets})$	FE-IV Instrument Sample $\log(\frac{AP}{Assets})$
Δsales/Assets,	0.285*** ooo	0.129	0.271***
if negative, 0 otherwise	(0.0672) [0.1008]	(0.1117) [0.2768]	(0.0752) [2.718]
lag1	0.233*** ooo	0.228**	0.266***
	(0.0657) [0.0873]	(0.1004) [0.2992]	(0.0751) [3.032]
lag2	0.076	0.043	0.095
	(0.0827) [0.1176]	(0.1471) [0.3735]	(0.0963) [2.188]
lag3	0.039	-0.101	-0.021
	(0.0620) [0.0860]	(0.1164) [0.4282]	(0.0743) [1.412]
lag4	0.010	-0.188**	-0.029
	(0.0407) [0.0493]	(0.0880) [0.2841]	(0.0624) [2.107]
log (1+firm age)	-0.150	-0.097	-0.167
	(0.1487) [0.2030]	(0.0818) [0.3705]	(0.1615) [2.818]
$[\log(1+\text{firm age})]^2$	0.041	0.012	0.044
	(0.0326) [0.0454]	(0.0131) [0.0625]	(0.0351) [0.8481]
(Current Assets-Cash)/Assets	1.696*** ooo	1.802*** ooo	1.711***
	(0.0813) [0.1149]	(0.1275) [0.3465]	(0.0904) [1.197]
lag1	0.163*** oo	0.355***	0.255***
	(0.0445) [0.0648]	(0.1114) [0.3305]	(0.0959) [0.9697]
lag2	0.137*** oo	0.045	0.052
	(0.0519) [0.0689]	(0.1012) [0.3876]	(0.0760) [1.514]
lag3	0.095** o	0.061	0.039
	(0.0405) [0.0504]	(0.0947) [0.3622]	(0.0769) [1.662]
lag4	0.058	0.253***	0.109*
	(0.0480) [0.0653]	(0.0824) [0.2684]	(0.0656) [1.612]
Inventories / Assets	0.697*** ooo	0.645***	0.660***
	(0.1107) [0.1441]	(0.1614) [0.4820]	(0.1181) [2.538]
lag1	-0.882*** ooo	-1.035*** o	-0.948***
	(0.0753) [0.1182]	(0.1224) [0.5669]	(0.1063) [1.517]
lag2	-0.240*** ooo	-0.128	-0.128
	(0.0655) [0.0839]	(0.1248) [0.3166]	(0.0973) [2.226]
lag3	-0.144*** oo	-0.264***	-0.147**
	(0.0536) [0.0657]	(0.0798) [0.6152]	(0.0712) [2.816]
lag4	-0.115	-0.214**	-0.146*
	(0.0706) [0.0913]	(0.0959) [0.3321]	(0.0809) [1.671]

Table 4.1 (continued)

	Fixed Effects Instrument Sample $\log\left(\frac{AP}{Assets}\right)$	2 SLS Instrument Sample $\log\left(\frac{AP}{Assets}\right)$	FE-IV Instrument Sample $\log\left(\frac{AP}{Assets}\right)$
Ret.Earnings / Assets	-0.003**	-0.005***	-0.003**
	(0.0014) [0.0151]	(0.0020) [0.0163]	(0.0013) [0.0181]
lag1	0.0003	-0.002*	0.0001
	(0.0007) [0.0029]	(0.0011) [0.0051]	(0.0007) [0.0085]
lag2	-0.0000	-0.002	-0.00005
	(0.0013) [0.0061]	(0.0015) [0.0101]	(0.0014) [0.0238]
lag3	-0.001	-0.002**	-0.0004
	(0.0008) [0.0028]	(0.0010) [0.0042]	(0.0008) [0.0060]
lag4	0.0004	-0.001	0.0004
	(0.0013) [0.0042]	(0.0013) [0.0064]	(0.0013) [0.0104]
T-Bill	0.014*** ^{ooo}	0.025***	0.019***
	(0.0014) [0.0021]	(0.0078) [0.0411]	(0.0057) [0.1325]
lag1	-0.001	-0.031	-0.017
	(0.0019) [0.0025]	(0.0189) [0.0567]	(0.0137) [0.1766]
lag2	0.002	0.006	0.005
	(0.0016) [0.0021]	(0.0070) [0.0427]	(0.0058) [0.1433]
lag3	0.003	-0.008	-0.006
	(0.0017) [0.0023]	(0.0104) [0.0616]	(0.0086) [0.2683]
lag4	-0.007*** ^{ooo}	-0.014	-0.015*
	(0.0016) [0.0020]	(0.0100) [0.0478]	(0.0088) [0.2072]
4 Lags of Regressors Included	Yes	Yes	Yes
Year and Quarter Dummies	Yes	Yes	Yes
4-digit SIC Industry Dummies	No	Yes	No
R-squared	0.23	0.22	0.15
Obs	107965	107965	107965
Firms	3798	3798	3798

Notes:

Tariff is used as instrument for comovement in the 2SLS and FE-IV columns. Standard errors in parentheses are robust to heteroskedasticity and serial correlation. Standard errors in brackets are bootstrapped and valid despite the presence of the generated regressor (comovement variable). Estimation assumes independence across firms. ***, **, and * denote respective significance at 1%, 5%,and 10% based on the standard errors given in parentheses. ^{ooo}, ^{oo}, and ^{o} denote respective significance at 1%, 5%,and 10% based on the standard errors given in brackets. Firm age isapproximated by the number of quarters present in the Compustat database.

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