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**Estimating the Effects of Finance Constraints
and Social Learning on Inventory Investment,
Trade Credit, and Capital Investment Decisions**

by

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A thesis submitted to
the faculty of Graduate Studies and Research
in partial fulfillment of
the requirements for the degree of

Doctor of Philosophy

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Abstract

Conventional theories often cannot explain the observed volatility in aggregate inventories and capital investment. Two types of information-based models may provide alternative explanations: finance/credit constraints, and social learning models. Information asymmetry problems can cause finance constraints whereby credit access is reduced at certain times. This may cause sharp changes in spending by constrained firms, and could account for fluctuations in aggregate spending. Social learning models describe agents learning from others. Widespread social learning can cause actions to be clustered together in time as agents attempt to benefit from watching others before acting. Abrupt changes can result due to small changes in underlying fundamentals if many agents suddenly act in response to others. Thus social learning models can generate large changes in aggregate spending.

The thesis tests three separate models of finance constraints and social learning. Chapters one and two test for finance constraints with inventory and trade credit data. Chapter four investigates social learning and investment by semiconductor plants.

I do not find that finance constraints affect inventory investment in a sample of publicly-traded Canadian manufacturing firms. However, with the much larger sample of Canadian firms used to study trade credit, I find clear evidence of credit constraints. Medium-wealth firms substitute trade credit for bank credit. A one standard deviation decrease in bank credit increases their trade credit use by 0.9%. The wealthy firms' trade credit usage is independent of bank credit, which implies that they are not finance-constrained. The poorest firms are constrained in both trade credit and bank credit. This

research suggests that from 1988 to 1998, most Canadian firms faced some degree of credit rationing, producing a procyclical pattern in aggregate trade credit use.

Social learning appears to influence semiconductor plants' decision to adopt new technology. A 1% increase in the number of other plants that have suspended their investment project generates a 3% increase in the probability of suspension by a plant adopting new technology. Firms investing in conventional technology seem to engage in a "war of attrition" since they are *less* likely to suspend their project if other suspensions occur.

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Chapter 1

Introduction

Over the business cycle, the most volatile components of aggregate spending are inventory investment and capital stock investment (Blinder and Maccini, 1991). A large literature begun by Fazzari, Hubbard and Peterson (1988) examines whether finance constraints due to information asymmetries between borrowers and lenders can explain the volatility in aggregate investment data. Firms whose activities are less well known to external lenders may face credit rationing or higher borrowing costs than firms without such information problems. Finance constraints are believed to bind more strongly during recessions or periods of contractionary monetary policy, and hence may generate decreases in investment spending by constrained firms. In this way, finance constraints could explain some of the observed volatility of investment and inventory spending.¹

Another class of information-based theories use social learning models to explain the boom and bust nature of capital investment and financial markets. Social learning theories explain phenomena such as herd behaviour and market crashes by looking at rapid changes in market sentiment when there is a sudden change in information available to the market, called information cascades.² If private information is initially widely dispersed among agents, they may delay their own actions in order to learn more about market conditions by observing what other market participants do (social learning). If a significant action is taken by a few or even one participant, market sentiment among others can change dramatically

¹ See references in Chapter two.

² This literature includes Banerjee (1992); Bikchandani et al (1992), Lee (1992); Chamley and Gale (1994); Caplin and Leahy (1994) and (1998); Hovarth et al (2001). See references in Chapter four.

and lead to a sudden change in behaviour, for example a large decrease in investment spending.

This thesis separately tests these two types of information theories, finance constraints and social learning, on firm level data. It consists of three empirical studies. Chapters two and three empirically test for the presence of finance constraints in Canadian markets using financial statement data from a panel of Canadian firms. In Chapter two, I examine inventory investment behaviour to see if there is evidence of finance constraints using Canadian data from Compustat. Firms are classified as being likely to have information problems based on age, size and bond ratings. I then compare the role of cash flow in explaining inventory investment for constrained versus unconstrained firms. Several papers study inventory investment and finance constraints, but this is the first study to do so with Canadian firm-level data.

Chapter three tests a new model of trade credit and credit rationing that arises when moral hazard problems exist. Trade credit is short term credit provided by a firm's suppliers. Despite very high implicit interest rates on this source of financing, trade credit is widely used. One possible explanation for the prevalence of trade credit is that many firms are constrained in their access to bank credit, and so use trade credit as a poor, but available substitute for bank credit. Although there is a sizable literature on trade credit, most of the empirical work has been done using U.S. or British data.³ Since the banking systems in Canada and the United States differ substantially, there may be differences in the use of trade credit. Using microdata from Statistics Canada's Financial and Taxation Statistics for Enterprises (FTSE) database, I test for the substitution of trade credit for bank loans among

³ I am aware of just one study that uses Canadian data, by Ross and Pike (1997), but they focus only on trade credit decisions faced by exporting firms. See Chapter three references.

firms of different wealth levels. This study makes use of a very large sample of Canadian firms, including many very small, privately-held firms. It is one of the first studies of trade credit to use a large panel of firms.

Social learning models may make a substantial contribution to our understanding of the how cyclical patterns that arise in many markets. The theory of social learning is relatively new, beginning in the early 1990s. As yet there have been very few tests of these theories on real data. The fourth chapter contains one of the first empirical studies of social learning and investment behaviour. Social learning models predict that agents can inefficiently delay actions such as initiating or suspending an investment project. This prevents the market from aggregating private information as efficiently as possible, and leads to a discontinuous pattern of activity whereby information cascades lead to market crashes. I test a social learning model developed by Caplin and Leahy (1994) using a unique international database on the construction and suspension of semiconductor fabricating plants. The semiconductor industry was selected as a case study because it is an economically important industry that has well known cycles of investment spending activity, and therefore has many of the features that are hard to explain with conventional models of investment.

Chapter 2

Finance Constraints and Inventory Investment

1. Introduction

Models of finance constraints attempt to explain how information asymmetries between borrowers and lenders can cause some profitable investment projects to remain unexploited. Information asymmetries in capital markets arise when firms have private information that cannot be costlessly observed by outside lenders. In their seminal work on finance constraints, Fazzari, Hubbard and Peterson (1988) show that such firms may have to pay a premium for external financing that is not fully collateralized by their internal funds. In finance constraints models, the higher costs of external financing cause firms with high information costs to finance more of their investment activities with their internal funds. Established firms with low information costs will have greater access to external funds, and therefore their investment activities are less dependent on their internal finances.

Finance constraints are believed to bind most strongly when interest rates rise and during recessions. At these times, collateral values weaken and internal funds decline. The premium on external finance rises for high-information-cost firms. To increase their liquidity, the constrained firms reduce investment spending and production, and therefore amplify the business cycle downturn. Similarly, positive economic shocks can cause constrained firms to have greater access to credit, which increases their investment and production, and further strengthens an expansion. These interactions are sometimes referred

to as “financial accelerator” effects.⁴

Binding finance constraints may affect various types of firm behavior: fixed capital investment spending, inventory investment spending, building market share, or R&D activity. Since inventories are more liquid than many other assets, one would expect finance constraints to be most apparent in inventory investment, and that during recessions, the most rapid and largest inventory disinvestment would occur in finance-constrained firms.

Blinder and Maccini (1991) observe that inventory investment is one of the most volatile components of GNP over the business cycle. They find that during U.S. recessions, the decline in inventory investment spending averaged 87% relative to the total decline in GNP. Table 1 shows similar calculations for Canadian recessions since 1947. The pattern is similar to Blinder and Maccini’s calculations. Inventory disinvestment during recessions appears to be more pronounced in Canada, since the average decline in inventory investment is almost 200%, or double, the decline in total output.

Recent debate in the literature on finance constraints has raised the issue of financial distress and its influence on tests for finance constraints using investment cash flow sensitivities (Kaplan and Zingales 1997, 2000; Fazzari, Hubbard and Peterson 2000). Povel and Raith (2001) develop a theoretical model of investment under both aspects of financial constraints: financial distress and asymmetric information.

Using Canadian firm-level data on inventory investment, this paper explores two empirical implications of the Povel and Raith model of investment under finance constraints. First, I examine the influence of negative cash flow observations on inventory investment.

⁴ See financial accelerator models discussed in Bernanke, Gertler and Gilchrist (1996); Bernanke and Gertler (1989, 1995), Gertler and Gilchrist (1994), Kashyap, Stein and Wilcox (1993) and Kiyotaki and Moore (1997). Older macroeconomics literature in this area includes Fisher (1933), and Gurley and Shaw (1955, 1960).

Second, I test for the presence of finance constraints due to information asymmetries between borrowers and lenders using firm age, the presence of a bond rating, and firm size as indicators of information asymmetry. This is the first paper to study finance constraints and inventory investment using Canadian data. The findings indicate that negative cash flow observations have a substantial effect on the sensitivity of inventory investment to cash flow. However, there is little evidence of finance constraints due to asymmetric information in the sample period, 1992:2 – 1999:4, since coefficients on cash flow are not statistically different across firm groups.

2. Recent Empirical Literature

Much of the empirical work on finance constraints faced by firms has focused on capital stock investment. Hubbard (1998) provides a survey of empirical literature on capital market imperfections and investment. These studies generally test the standard model of Fazzari, Hubbard and Peterson (1988) by comparing the sensitivities of investment to cash flow across groups of firms. These firms are categorized *a priori* as finance-constrained or unconstrained, based on characteristics that proxy for information asymmetry. Characteristics commonly used to categorize firms include: bond ratings, dividends, age, size and membership in industrial groups. The majority of studies find evidence supporting the theory that finance constraints reduce investment by firms with high information costs.⁵

Nevertheless, an important debate on cash flow-investment sensitivities has arisen in the investment literature. Several recent studies do not find the predicted differences in cash flow sensitivities; in some cases, unconstrained firms' investment is *more* sensitive to cash

⁵Examples include, among others, Fazzari, Hubbard and Peterson (1988), and Whited (1992), who use data from the United States; Schaller (1993) who tests Canadian data, and Hoshi, Kashyap, and Scharfstein (1991) who test finance constraint models on Japanese panel data.

flow than financially constrained firms (Allayannis and Mozumdar, 2001; Cleary, 1999; Kaplan and Zingales, 1997; and Gilchrist and Himmelberg, 1995). Allayannis and Mozumdar specifically examine the influence of negative cash flows in tests for investment-cash flow sensitivities. They find that negative cash flow observations can generate findings that contradict the standard theory. However, once they remove negative cash flow observations, the investment-cash flow sensitivities do not differ between the finance constraint categories. Povel and Raith (2001) develop a theoretical model of finance constraints that helps to explain some of these contradictory findings. I test some of the implications of Povel and Raith's model using methods similar to those of Allayannis and Mozumdar.

In the inventory investment literature, the results more clearly support the theory of the finance constraints. Papers by Carpenter, Fazzari and Peterson (1998, 1994), Guariglia (1999), Zakrajsek (1997), Gertler and Gilchrist (1994), Kashyap, Lamont and Stein (1994), and Kashyap, Stein and Wilcox (1993) examine inventory investment data for evidence of finance constraints. These papers all test some form of partial inventory adjustment model. The partial adjustment inventory model is augmented with financial variables that proxy for internal finance such as cash flow, interest coverage ratio, liquidity ratios, or other financial ratios. These studies typically feature firm-level data analyzed over periods of recession or periods where monetary policy was known to be restrictive.⁶ These are periods when finance constraints are most likely to bind. The augmented inventory investment model is estimated separately for the finance-constrained and unconstrained groups of firms. Most authors focus on manufacturing firms; the exceptions are Kashyap, Stein and Wilcox (1993) who use aggregate data, and Zakrajsek (1997) who studies retail sector inventories. Six of the seven

⁶ Kashyap, Stein and Wilcox (1993) and Gertler and Gilchrist (1994) do not use firm-level data; instead they use industry level data or aggregate data.

papers analyze data from the United States; Guariglia tests for finance constraints using data from the United Kingdom. The current paper is one of the first inventory studies to explicitly consider the effect of negative cash flow observations.

Previous studies on inventory investment and finance constraints find that the financial variables, such as cash flow or liquidity, have significant and larger coefficients for firms in the finance-constrained group compared to the unconstrained firms. Kashyap, Stein and Wilcox (1993) also find that financial variables are significant in explaining inventory investment using aggregate data. Although the evidence in the literature on *fixed* investment and finance constraints is mixed, *inventory* investment research to date is less ambiguous. Existing studies more clearly support the view that finance constraints lead to a positive relationship between cash flow and inventory investment.

3. Data Description

The data consist of Compustat data on quarterly financial statement items from publicly-traded Canadian manufacturing firms.⁷ There are a total of 2,211 observations on 166 firms for the period 1992:2—1999:4. Firms with fewer than six consecutive quarters of data are not included. The number of observations on each firm varies from 6 quarters to 30 quarters, so the panel is unbalanced. The average firm in the dataset has 13 quarters of data. I also omit observations where there is zero inventory investment for three or more consecutive quarters, since zero inventory investment may indicate a temporary shutdown or disruption in the firm's activities. Observations are also excluded for periods of merger

⁷ The data come from Compustat's Research Insight North American database of firms actively traded on Canadian stock exchanges as of June, 2000. This dataset includes companies that were publicly traded over the whole period and those that began trading at some point during the period. However, any firms that stopped trading during the period are not included. Firms are considered to be in the manufacturing sector if their primary (U.S.) SIC assigned by Compustat lies in the range 2000 – 3999.

activity, as identified by Compustat, since mergers may disrupt inventories or generate other anomalies. The variables of interest for regression testing of the finance-constraints hypothesis are: inventories, cash flow, sales and total assets. These variables are explained in more detail in the data appendix. To ensure the regression results are not driven by a few outlying observations, the upper and lower one percent values of observations for inventory stock, sales, and cash flow are removed.

As in the other studies on finance constraints using panel data, firms are categorized as likely to be finance-constrained or not likely to be finance-constrained. Three different criteria determine the constrained and unconstrained groups: age; the presence of a bond rating; and size. Based on its date of incorporation, a firm is classified as young at time t if its age is lower than the median firm in the sample at time t .⁸ An old firm has age equal to or greater than the median age of firms in the sample at time t . Depending on the composition of the sample at a given time, a firm may be classified as young in one period and old in another. Firms that are classified as young are expected to have more costly asymmetric information problems with borrowers and, *a priori*, are assumed to be more finance-constrained.

Bond ratings provide a second way of splitting the sample to reflect differences in capital market information asymmetry problems. Firms that have their corporate bonds rated by a bond rating agency are considered likely to face fewer finance constraints than unrated firms, since there is more information available to lenders about the quality of the rated firms' investment opportunities. Firms are classified as having a bond rating if they had

⁸ I use the Financial Post/Mergeant FIS Online database for data on the year of incorporation. Where the FIS database could not provide the year of incorporation, I used company websites and the SEDAR website from the Canadian Securities Administrators. (SEDAR is an Internet database of Canadian publically traded firms' financial statements are electronically filed, similar to the EDGAR database in the U.S.)

a rating at the end of the sample period, based on the ratings available from the Dominion Bond Rating Service website (as of June 2001) and the ratings of Standard and Poor's as shown in the *Financial Post Corporate Bond Record 1999*. Firms do not switch categories with respect to bond rating over the period. Using this method, 41 of the 166 firms in the sample are rated, and 125 are unrated.

Finally, I split the firms on the basis of size. Small firms, defined as firms with total assets of less than the median value of total assets in period t , are considered likely to be finance-constrained. Firms with total asset values greater than or equal to the median value are considered large and likely to be unconstrained. As in the split by age, firms may change size categories depending on the size of other firms in the sample in given period.

Tables 2 and 3 present summary statistics for the full sample and subsamples when the sample is split by age, the presence of a bond ratings, and the size of the firm. One of the most important features of the data is the prevalence of negative cash flow observations; 93 of the 166 firms have at least one quarter with negative cash flow, and 32 firms have four or more quarters with negative cash flow. In total, there are 342 firm-quarter observations where cash flow is negative, accounting for 15.5% of the full sample of 2,211 firm-quarter observations. Allayannis and Mozumdar find 8% of firm-year observations include negative cash flows in a sample of U.S. manufacturing firms over the period 1977—1996.

The absolute levels of all the variables differ significantly between the groups of firms, regardless of whether age, bond ratings or size characteristics are used to split the sample. The firms in the groups expected to be finance-constrained (young, unrated or small) have much lower levels of total assets, inventory stock, sales and cash flow. However,

scaling the variables by total assets reduces the differences across finance constraint categories considerably.

The mean of cash flow to total assets (CF/TA), shown at the bottom of each table, is much smaller for the firms in the finance-constrained categories relative to firms in the unconstrained categories. The mean of CF/TA is 0.005 for young firms, which is one quarter of the mean value of CF/TA for old firms, 0.020. In Table 3, this ratio is 0.01 for unrated firms, or about half the mean CF/TA of rated firms, 0.019. The average small firm has a negative cash flow to asset ratio, -0.001, compared to the much higher ratio of 0.022 for the average large firm. However, the standard errors are also considerably larger for the finance-constrained firms and there are often fewer observations per firm for young, unrated or small firms.

The dependent variable in the regressions is the ratio of inventory investment to total assets ($\Delta N/TA$). This ratio is similar across young and old firms, but unrated firms and small firms have larger ratios than their counterparts for this variable. It is interesting that two types of firms expected to be finance constrained, the unrated and the small firms, tend to have larger inventory investment ratios despite lower average cash flow ratios. The ratio of sales to inventory stock (S/N) is used to reflect the firm's long run target inventory. The mean of the sales to inventory ratios do not differ substantially across finance-constraint categories, suggesting similar inventory targets for different categories of firms.

4. Theoretical Model of Finance Constraints

Povel and Raith (2001) model a firm's optimal level of investment under finance constraints. Their model provides a theoretical basis for some of the recent contradictory findings from empirical work on fixed investment and finance constraints. Two important

features of their model make it well-suited to potentially explain the behavior of firms in the sample. First, it assumes that the firm is able to determine the scale of its investment and many other details such as quality of inputs, rather than making the usual assumption that the firm faces a binary choice to undertake or not undertake a single investment project. Scalable investment seems to be a more appropriate description of inventory investment than an all-or-none investment project. The second feature of interest is that internal funds (often operationalized as cash flow) may be negative. This is useful in the context of my data which has a large number of observations with negative cash flow.

The main result Povel and Raith prove is that the firm's optimal investment function is U-shaped over the range of feasible levels of internal funds. The solid line in Figure 1 shows this relationship for a firm with no information asymmetry problems. The first best level of investment, I^* , is undertaken if the firm can fund the project internally with its own cash flow, i.e. when CF equals I^* . With cash flow positive and less than I^* , the firm's optimal investment level is less than I^* , but positive and increasing in cash flow. This is consistent with earlier models based on Fazzari *et al.* (1988) that imply a positive, monotonic relationship between investment and internal funds. However, in the range where internal funds are negative, investment may rise or fall as cash flow increases. In the most extreme case, the firm's cash flow is at the lower bound where it is still possible to obtain financing, $\underline{CF}$. In this case, the optimal level of investment would be as high as the first best level, I^* . This U-shaped investment-cash flow relationship occurs because there are two opposing effects at work: a cost effect and a revenue effect. The cost effect is that higher levels of investment increase the firm's repayment costs and thereby raise its risk of default and liquidation. The revenue effect is that higher levels of investment generate more revenue.

The revenue effect increases the firm's chance of survival and lowers the marginal cost of debt finance.

Povel and Raith prove that the cost effect dominates when the firm has positive or slightly negative cash flow, and that the revenue effect dominates when the firm has significantly negative cash flow. The dominance of the cost effect implies the familiar, positive monotonic investment-cash flow relationship such that an increase in cash flow leads to an increase in investment.

It is also possible that the revenue effect dominates. If the firm has substantially negative internal funds, part of its borrowing must be used to offset its negative cash flow (e.g. to pay down existing debt, or to cover fixed costs). As cash flow becomes more negative, a larger share of any loan must be used to cover these non-revenue-generating expenses. However, for the investor to break even, the firm must be able to generate revenue. Therefore, the firm must increase the scale of its investment, even as CF falls, to generate enough revenue to repay the loan. In this scenario, the revenue effect dominates and there is a negative relationship between cash flow and investment. In the region where the investment function reaches a minimum, it is relatively insensitive to changes in cash flow.

Povel and Raith also demonstrate that a U-shaped investment function occurs when there is asymmetric information between the firm and the outside investor. The dashed line in Figure 1 shows the effects of information asymmetry on the investment function. As the degree of information asymmetry increases, the investment function becomes steeper almost everywhere except in the region of the minimum. Asymmetric information leads to increased sensitivity of investment to cash flow.

This model yields at least two testable implications. In the presence of both positive and negative cash flow observations, the model predicts the investment cash flow function will be non-monotonic. One can test for non-monotonicity by removing the negative cash flow observations. This should result in a positive monotonic relationship between cash flow and investment for all firms. A second simple test can indicate the influence of information asymmetry in capital markets on investment. Firms believed to have a higher degree of asymmetric information are predicted to have larger slope coefficients on the cash flow variable than firms with fewer asymmetric information problems.

5. Regression Equation and Estimation Results

I use a regression equation based on the partial adjustment model for inventories from Lovell (1961). Partial adjustment inventory models describe a process of inventory investment whereby each firm has a desired or “target” level of inventories. In a given period, adjustment costs prevent the firm from fully adjusting actual inventories to the target level. Augmenting the model with variables to reflect the firm’s financial situation is a common technique to test for finance constraints. In this specification, cash flow captures the effect of a firm’s financial condition on its inventory investment.⁹ Since the data include some observations with negative cash flow, I do not transform the data using logs, but rather each firm’s balance sheet variables (inventories, sales, and cash flow) are scaled by its total assets for the same time period. The following model for inventory investment is used:

⁹ This model is based on those of Guariglia (1999), Gertler and Gilchrist (1994), and Kashyap, Stein and Wilcox(1993).

$$\begin{aligned}
 (1) \quad \Delta N_{it} = & \beta_0 + \beta_1 \left[\frac{E_{t-1} S_{it}}{N_{it-1}} \right] + \beta_2 r_{t-1} + \beta_3 CF_{it-1} + \beta_4 \sum_{k=1}^2 \Delta N_{it-k} \\
 & + \beta_5 \sum_{k=1}^2 \Delta S_{it-k} + \beta_6 \sum_{k=1}^2 \Delta r_{it-k} + \beta_7 \sum_{k=1}^2 \Delta CF_{it-k} + \nu_i + \nu_t + \varepsilon_{it}
 \end{aligned}$$

The terms N_{it} , S_{it} and CF_{it} denote firm i 's real inventory, sales and cash flow respectively, for period t .¹⁰ The real interest rate, r , is calculated as the prime rate less the inflation rate using the GDP deflator. The dependent variable, inventory investment, is the first difference of inventories, $N_{it} - N_{it-1}$. This specification includes both long run and short run effects, giving it an error-correction format. The effects of the firm's long run target inventory stock are captured by the first three regressors (in levels): the ratio of expected sales to current inventory levels, one lag of the real interest rate and one lag of cash flow.¹¹ Along with the level terms, lagged differences of inventories, sales, interest rate and cash flow are included to capture the effect of short run dynamics. The error term consists of the last three terms in the equation. The effects of firm-specific characteristics which do not vary with time are represented by ν_i . Time-specific effects, denoted ν_t , reflect the influence of common shocks for a given time period such as business cycle conditions. A full set of time dummy variables capture the time-specific effects. The term ε_{it} denotes the idiosyncratic component of the error term.

Since lagged dependent variables are included as regressors and there are a relatively small number of time periods for each firm, both the fixed effects and GLS random effects estimators will be inconsistent. Their inconsistency arises from the correlation of the lagged

¹⁰ Each of these variables is first divided by firm i 's real total assets in the same period, before any further transformations, such as differencing, occur.

¹¹ In estimating equation (1) actual sales in period $t-1$ is used as a proxy for expected sales in period t .

dependent variable with the fixed effect component of the error term.¹² First differencing removes the firm-specific effect, shown in equation (2).

$$(2) \quad \begin{aligned} \Delta \Delta N_{it} = & \beta_1 \Delta \left[\frac{E_{t-1} S_{it}}{N_{it-1}} \right] + \beta_2 \Delta r_{t-1} + \beta_3 \Delta CF_{it-1} + \beta_4 \sum_{k=1}^2 \Delta \Delta N_{it-k} \\ & + \beta_5 \sum_{k=1}^2 \Delta \Delta S_{it-k} + \beta_6 \sum_{k=1}^2 \Delta \Delta r_{it-k} + \beta_7 \sum_{k=1}^2 \Delta \Delta CF_{it-k} + \Delta v_i + \Delta \varepsilon_{it} \end{aligned}$$

Equation (2) is estimated using the Arellano-Bond (1991) GMM estimator. The instruments include: $\Delta S_{it-1}/N_{it-1}$, Δr_{it-1} , ΔCF_{it-1} , two lags of $\Delta \Delta S_{it}$, $\Delta \Delta r_{it}$, $\Delta \Delta CF_{it}$, $\Delta \Delta N_{it-3}$ and further lags, as well as the differenced time dummies. The consistency of the Arellano-Bond estimator requires that there is no second-order autocorrelation in the residual, so the results of an m2 test are reported in the results below. The results for a Sargan test of the validity of the over-identifying restrictions used by the Arellano-Bond estimator are also reported.¹³

5.1 Negative Cash Flow Observations

Table 4 presents the results of the simple test of the effect of negative cash flow on the sensitivity of inventory investment to cash flow. It compares the estimation results when all the cash flow observations are included (the first column) to the estimates obtained when negative cash flow observations are discarded (the second column). The m2 test statistics in both columns imply that one cannot reject the hypothesis of no second order autocorrelation in the residuals, so the estimates are consistent. Similarly, the Sargan tests

¹² See Baltagi (1995) p.125-26.

¹³ Since the Sargan test tends to over-reject the null hypothesis of valid instruments in the one-step Arellano-Bond estimator, the two-step estimator results are reported for the m2 and Sargan tests. However coefficient estimates and standard errors presented are from the one-step estimation procedure since Arellano and Bond recommend using one-step results for inference. Note that I assume all variables except the lagged dependent variable are exogenous. It may be more accurate to treat sales and cash flows as pre-determined, a weaker assumption than exogeneity. However, this would require more observations per firm than were available. Stata software was used to perform the regressions.

indicate that the moment restrictions used in the model are valid, and that the model is correctly specified for both regressions.

The theoretical model does not clearly imply the nature of the short run movements in inventory investment in response to changes in cash flow. Therefore the primary variable of interest is the first regressor in each table, ΔCF , which is intended to capture the long run nature of the inventory investment-cash flow sensitivity. The first column contains only two variables that are significantly different from zero: the long run sales to inventory ratio, and the lags of the dependent variable. When negative cash flow observations are included in the regression, the cash flow variables are not significantly different from zero, which is consistent with changes in slope over different regions of a U-shaped relationship between investment and cash flow. When the negative cash flow observations are removed, the long run cash flow term has much a larger, positive coefficient, 0.38, which is significant at the 1% level.

Tables 5 through 7 show the regression results for estimating equation (2) when the sample of firms is split by age, bond rating or size respectively. In this set of tables the first two columns of each table contain the regression results with all cash flow observations included. The third and fourth columns show the regression results when negative cash flow observations are removed. In each group of firms the coefficient on ΔCF increases when the negative cash flow observations are removed. For young, unrated, small and large firms, ΔCF is not significant when all observations are considered, but removing negative cash flows leads the ΔCF term to become significant. Old firms' long term cash flow coefficient was significant at the 10% level in the initial regression, but the coefficient more than doubles to 0.585 which is significant at the 1% level in the regression without negative cash

flows. Only the estimates for rated firms show little change in the ΔCF coefficient, 0.267 to 0.273, and the coefficient is positive and significant at the 1% level in both regressions.

The regression results with and without negative cash flow observations suggest that when firms are not undergoing financial distress, inventory investment increases as cash flow increases. These findings support the first prediction of the Povel and Raith model and is consistent with the results of similar tests by Allayannis and Mozumdar using data on fixed investment.¹⁴

5.2 Finance Constraints and Asymmetric Information

The primary concern in the finance constraints literature is the effect of asymmetric information in capital markets on investment behavior. Tables 5 through 7 show the estimation results when firms are grouped *a priori* to reflect information asymmetries. Ignoring the negative cash flow observations, the Povel and Raith model and earlier models of asymmetric information in capital markets imply that the young, unrated and small firms would have positive and significant coefficients on the cash flow term, and that the cash flow coefficients for these firms would be larger than the cash flow coefficients estimated for the old, rated and large firms. Table 5 compares young and old firms. The point estimates on the long run cash flow coefficient is actually larger for the old firms (0.585) than for the young firms (0.278). However, the difference in the point estimates for the ΔCF coefficient for young and old firms is not statistically significant. Similarly, in the regressions with only non-negative cash flow observations, the estimated cash flow coefficients are nearly identical

¹⁴ The long run relationship between inventory investment and cash flow is the primary concern here. However, in several regressions the second differences of the cash flow term, which are intended to show the influence of short run dynamics, have negative and significant coefficients. This is somewhat puzzling but similar conflicting signs between long run and short run cash flow variables were found in Zakrajsek (1997).

for unrated and rated firms, 0.283 and 0.273 respectively.¹⁵ These estimates suggest there is no evidence of finance constraints due to asymmetric information when I split the sample by age or bond rating. Allayannis and Mozumdar obtain similar results. Testing the sensitivity of inventory investment to coverage ratio, Guariglia (1999) finds that the U.K. data on total inventories do not show significant differences between finance constraint groups when the sample is split based on financial ratios (coverage, and net leverage ratio). However, she does find evidence supporting the predictions of finance constraints models when she uses cash flow rather than coverage ratio as a proxy for the financial health of the firm.

Table 7 contains the estimates of inventory investment-cash flow sensitivities when the sample is split by size. Here, the findings also contradict the theoretical models since large firms' inventory investments appear to depend more on cash flow than do the investments in inventories made by small firms. The coefficient on ΔCF for small firms is 0.365, which is significantly less than the estimate of 0.464 for large firms. These findings are similar to those of Cleary (1999) who finds that the least finance-constrained firms had the largest fixed investment-cash flow sensitivities.

Overall, the results here do not support the view that information asymmetries generate greater sensitivity between inventory investment and cash flow.¹⁶ Moreover, it appears that the ongoing debate about cash flow sensitivities in the fixed investment literature also extends to inventory investment.

¹⁵ To test whether the coefficients on ΔCF are statistically different between young and old firms, I estimate the model for the full sample including a dummy variable *YOUNG* and interacting all the regressors with the dummy variable. I then test whether the dummy variable and the interaction variable $\Delta CF * YOUNG$ are jointly equal to zero. The p-value for this F test is 0.42, indicating no statistical difference. The same method and tests for bond ratings generate an F test with p-value of 0.159, indicating statistical difference only at the 15.9% level. The test for small versus large firms has a p-value of 0.00, which implies that the cash flow coefficients are significantly different for these groups of firms.

¹⁶ Similar regressions using OLS and fixed effects (not shown) estimates generate the same conclusions.

The findings here differ from most of the previous research on inventory investment and finance constraints, but the period under study also differs. Most of the previous inventory papers have explicitly focused on recessions or low growth periods. One possible reason that I do not find evidence of finance constraints due to information asymmetries is the sample period. The latter years of the 1990s were a period of a strong business cycle expansion, a time when finance constraints may not bind. Moreover, during this period there may have been a speculative bubble in financial markets, which could have meant unusually generous access to capital for firms that one expects to be finance-constrained, such as young start-up firms. Allayannis and Mozumdar demonstrate that the sensitivity of investment to cash flow has declined over the period 1977—1996. They suggest that improvements in information available to capital markets or an increase in the supply of funds to primary capital markets may have improved the access to external funds for smaller and younger firms. In the inventory literature, Carpenter, Fazzari and Peterson (1994) also observe smaller coefficients on cash flow variables in the period 1988—1992 compared to earlier periods they studied, 1981—83 and 1984—1988. They attribute the reduction in sensitivity of inventory investment to the changes in business practice such as the introduction of just-in-time inventory management.

6. Conclusions

This paper contributes to the research examining the effect of financial variables on investment, including inventory investment. I estimate an error correction model for inventory investment augmented with cash flows. An important factor that has only recently begun to be studied is the effect of negative cash flow observations. Negative cash flow can be interpreted as evidence of financial distress. Povel and Raith demonstrate that the

relationship between inventories and cash flow in the presence of negative cash flow is a non-monotonic, U-shaped function, contrary to earlier linear models. The regression model is first estimated with all cash flow observations and then with negative cash flows removed. The findings of this paper indicate that Povel and Raith's model also extends to inventory investment, since cash flow coefficients are positive and significant only when negative cash flow observations are dropped. If sufficient observations with negative cash flows were available, the model could be estimated for these observations only, which should yield negative and significant coefficients on cash flow coefficients.

A second set of regressions are conducted to test for finance constraints due to information asymmetries between borrowers and lenders. These regressions estimate the model separately for old versus young firms; bond-rated versus unrated firms; and large versus small firms. In each pair of regressions, the latter group of firms is expected to be finance constrained. However, the findings do not conform to the predictions of the theory. Once the negative cash flow observations are removed, there is no statistically significant difference between estimated cash flow coefficients for young and old firms, nor for rated and unrated firms. The cash flow coefficient estimates are significantly different between large firms and small firms, but the findings are opposite the theoretical prediction, since the estimated cash flow coefficients are larger for large firms than for small firms. Therefore, information asymmetries between borrowers and lenders do not seem to have generated a stronger link between cash flow and inventory investment for Canadian manufacturing firms over the sample period, 1992:2—1999:4. Previous work on inventory investment has mostly supported theories of asymmetric information and finance constraints, but the findings here

show that some of the puzzles noted in the fixed investment finance constraints literature also arise with inventory investment.

Further research could build on these findings by using data for a longer time period, since some authors find that the effect of finance constraints may be weakening in recent years. Other sectors of the economy may have more volatile inventory investment than the manufacturing sector, so additional inventory studies that examine other sectors would also be helpful.

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Table 1: Inventory Investment in Canadian Recessions

Real GDP Peak to Trough	Change in Real GDP	Change in Inventory Investment	Change in Inventory Investment as a % of Change in Real GDP
1947:2—1948:1	-1,847	-4,577	248%
1951:1—1951:3	-3,484	-937	27%
1956:4—1958:1	-1,963	-10,805	550%
1969:4—1970:2	-2,458	-3,083	125%
1980:1—1980:3	-3,497	-12,401	355%
1981:2—1982:4	-32,360	-26,194	81%
1990:1—1991:1	-21,608	-588	3%
Average	-9,606	-6,598	198%

* Millions of 1992 Canadian dollars. Source: Statistics Canada Cat.13-355 for the period 1946—1986, and Cat. 13-001 for the period 1987—1991. All figures converted to 1992\$ using the GDP deflator. Recession dates based on two consecutive quarters of negative GDP growth, identified by Cross(1996).

Table 2: Summary Statistics, Sample Split By Age of Firm, millions of 1992 dollars

	Full Sample 166 firms 2,211 obs.	Young Firms 94 firms 980 obs.	Old Firms 89 firms 1,231 obs.
Total Assets (<i>TA</i>)			
Mean	1,920.33	628.60	2,948.68
Std. Deviation	4,224.31	1,164.96	5,347.39
Inventory Stock (<i>N</i>)			
Mean	259.42	60.06	418.12
Std. Deviation	621.26	108.97	791.93
Sales (<i>S</i>)			
Mean	389.18	117.06	605.82
Std. Deviation	782.42	208.60	979.45
Cash Flow (<i>CF</i>)			
Mean	35.35	11.15	54.61
Std. Deviation	80.05	36.08	98.19
Inventory / Total Assets (<i>N/TA</i>)			
Mean	0.165	0.156	0.173
Std. Deviation	0.098	0.095	0.100
Inventory Investment / Total Assets ($\Delta N/TA$)			
Mean	0.004	0.004	0.004
Std. Deviation	0.029	0.035	0.023
Sales / Inventory Stock (<i>S/N</i>)			
Mean	2.150	2.248	2.072
Std. Deviation	2.237	2.833	1.609
Sales / Total Assets (<i>S/TA</i>)			
Mean	0.255	0.241	0.266
Std. Deviation	0.123	0.133	0.113
Cash Flow / Total Assets (<i>CF/TA</i>)			
Mean	0.013	0.005	0.020
Std. Deviation	0.044	0.056	0.031

Source: Author's calculations from Compustat data. The total number of firms and observations for the subsamples do not add to totals for the full sample since a firm may shift categories.

**Table 3: Summary Statistics, Sample Split by Bond Rating and by Size of Firm
millions of 1992 dollars**

	Unrated 125 firms 1,429 obs.	Rated 41 firms 782 obs.	Small 104 firms 878 obs.	Large 88 firms 1,333 obs.
Total Assets (<i>TA</i>)				
Mean	458.39	4,591.84	65.49	3,142.05
Std. Deviation	1,034.23	6,122.34	61.90	5,083.63
Inventory Stock (<i>N</i>)				
Mean	58.852	625.921	12.679	421.93
Std. Deviation	107.266	928.989	14.571	757.41
Sales (<i>S</i>)				
Mean	123.30	875.05	18.49	633.35
Std. Deviation	241.21	1,122.57	20.91	930.15
Cash Flow (<i>CF</i>)				
Mean	10.37	80.99	1.07	57.92
Std. Deviation	36.01	111.96	3.16	96.65
Inventory Stock / Total Assets (<i>N/TA</i>)				
Mean	0.179	0.140	0.195	0.146
Std. Deviation	0.103	0.082	0.112	0.081
Inventory Investment / Total Assets ($\Delta N/TA$)				
Mean	0.004	0.003	0.005	0.003
Std. Deviation	0.034	0.017	0.040	0.018
Sales / Inventory Stock (<i>S/N</i>)				
Mean	2.108	2.227	1.856	2.343
Std. Deviation	1.844	2.816	1.691	2.515
Sales / Total Assets (<i>S/TA</i>)				
Mean	0.282	0.206	0.268	0.247
Std. Deviation	0.131	0.088	0.133	0.115
Cash Flow / Total Assets (<i>CF/TA</i>)				
Mean	0.010	0.019	-0.001	0.022
Std. Deviation	0.053	0.017	0.064	0.020

Source: Author's calculations from Compustat data. The total number of firms and observations for the subsamples do not add to totals for the full sample since a firm may shift categories.

Table 4: Regression Results for Full Sample of Firms
Regressions Using All Cash Flow Observations versus Non-negative Cash Flow
Observations Only

	All Cash Flow Observations	Non-negative Cash Flow Observations Only
	Full Sample	Full Sample
	166 firms	135 firms
	2,211 obs.	1,475 obs.
$\Delta CF_{it-1} / TA_{it-1}$	0.046 (0.069)	0.380*** (0.141)
$\Delta S_{it-1} / N_{it-1}$	0.008*** (0.003)	0.012*** (0.002)
Δr_{t-1}	-0.002 (0.004)	0.005 (0.003)
$\Sigma \Delta \Delta N_i / TA_i$	-0.144* (0.079)	-0.323*** (0.079)
$\Sigma \Delta \Delta S_i / TA_i$	-0.032 (0.055)	-0.024 (0.036)
$\Sigma \Delta \Delta CF_i / TA_i$	-0.087 (0.077)	-0.523*** (0.195)
$\Sigma \Delta \Delta r$	-0.001 (0.005)	-0.006 (0.004)
Sargan test	130.5 (1.00)	105.2 (1.00)
m2 test	0.80 (0.42)	1.45 (0.15)

The dependent variable is the first difference of inventory investment divided by total assets in period t , $\Delta \Delta N_{it} / TA_{it}$. $\Sigma \Delta \Delta X$ provides the sum of coefficients for two lags of the second difference of X . All equations are estimated with the Arellano-Bond GMM estimator with $\Delta S_{it-1} / N_{it-1}$, Δr_{t-1} , $\Delta CF_{it-1} / TA_{it-1}$, two lags of $\Delta \Delta S_{it} / TA_{it}$, $\Delta \Delta CF_{it} / TA_{it}$, $\Delta \Delta r_t$ and $\Delta \Delta N_{it-3} / TA_{it-3}$ and further lags as instruments. Differenced time dummies are also included in the instrument set. Standard errors are shown in parentheses. Standard errors and test statistics for coefficients are robust to heteroskedasticity. Significance of coefficients at various levels is indicated by *** for 1% level; ** for 5% level; and * for the 10% level. Two-step results for the Sargan test and m2 test are reported with p-values in parentheses. One-step results are presented for coefficients and test statistics.

Table 5: Regression Results with Sample Split by Age of Firms
Regressions Using All Cash Flow Observations versus Non-negative Cash Flow
Observations Only

	All Cash Flow Observations		Non-negative Cash Flow Observations Only	
	Young Firms 94 firms 980 obs.	Old Firms 89 firms 1,231 obs.	Young Firms 78 firms 621 obs.	Old Firms 72 firms 854 obs.
$\Delta CF_{it-1} / TA_{it-1}$	-0.060 (0.069)	0.248* (0.135)	0.278* (0.161)	0.585*** (0.185)
$\Delta S_{it-1} / N_{it-1}$	0.006*** (0.002)	0.018*** (0.005)	0.008*** (0.003)	0.009*** (0.003)
Δr_{t-1}	-0.006 (0.006)	0.001 (0.003)	-0.008** (0.003)	-0.001 (0.002)
$\Sigma \Delta \Delta N_i / TA_i$	-0.204* (0.108)	-0.136 (0.102)	-0.318*** (0.105)	-0.390*** (0.096)
$\Sigma \Delta \Delta S_i / TA_i$	-0.055 (0.064)	-0.079 (0.060)	-0.042 (0.047)	-0.060 (0.053)
$\Sigma \Delta \Delta CF_i / TA_i$	0.045 (0.072)	-0.190 (0.154)	-0.423 (0.271)	-0.467* (0.257)
$\Sigma \Delta \Delta r$	0.001 (0.005)	0.001 (0.002)	0.000 (0.005)	0.002 (0.003)
Sargan test	58.91 (1.00)	54.44 (1.00)	41.90 (1.00)	35.63 (1.00)
m2 test	1.27 (0.20)	-1.11 (0.27)	0.69 (0.49)	-0.52 (0.61)

See notes to Table 4.

Table 6: Regression Results with Sample Split by Bond Rating
Regressions Using All Cash Flow Observations versus Non-negative Cash Flow
Observations Only

	All Cash Flow Observations		Non-Negative Cash Flow Observations Only	
	Unrated Firms 125 firms 1,429 obs.	Rated Firms 41 firms 782 obs.	Unrated Firms 94 firms 923 obs.	Rated Firms ^a 40 firms 488 obs.
$\Delta CF_{it-1} / TA_{it-1}$	0.055 (0.069)	0.267*** (0.102)	0.283* (0.165)	0.273*** (0.104)
$\Delta S_{it-1} / N_{it-1}$	0.008*** (0.003)	0.007** (0.003)	0.012*** (0.003)	0.000 (0.001)
Δr_{t-1}	-0.004 (0.006)	-0.002 (0.002)	-0.003 (0.004)	-0.002 (0.002)
$\Sigma \Delta \Delta N_i / TA_i$	-0.169** (0.085)	-0.229** (0.101)	-0.358*** (0.080)	-0.411*** (0.091)
$\Sigma \Delta \Delta S_i / TA_i$	-0.038 (0.065)	-0.093** (0.044)	-0.022 (0.040)	0.012 (0.042)
$\Sigma \Delta \Delta CF_i / TA_i$	-0.081 (0.081)	-0.291*** (0.117)	-0.364 (0.230)	-0.048 (0.279)
$\Sigma \Delta \Delta r$	-0.003 (0.006)	0.002 (0.002)	0.001 (0.004)	0.005 (0.003)
Sargan test	89.70 (1.00)	5.34 (1.00)	63.77 (1.00)	1.81 (1.00)
m2 test	0.45 (0.66)	-0.88 (0.38)	1.06 (0.29)	-1.89 (0.06)

a. The m2 test for original regression equation showed that the residuals are AR(2). I correct for this by using the same long run variables as the original instrument set, but using the earlier lags ($t-2$ and $t-3$) of the short run variables for sales, cash flow and interest rates as instruments. See Table 4 notes.

Table 7: Regression Results with Sample Split by Size of Firm
Regressions Using All Cash Flow Observations versus Non-negative Cash Flow
Observations Only

	All Cash Flow Observations		Non-Negative Cash Flow Observations Only	
	Small Firms 104 firms 878 obs.	Large Firms ^a 86 firms 1,231 obs.	Small Firms 77 firms 582 obs.	Large Firms 75 firms 893 obs.
$\Delta CF_{it-1} / TA_{it-1}$	0.021 (0.077)	0.046 (0.032)	0.365** (0.161)	0.464*** (0.144)
$\Delta S_{it-1} / N_{it-1}$	0.010*** (0.004)	0.004** (0.002)	0.008*** (0.002)	0.009*** (0.004)
Δr_{t-1}	-0.002 (0.008)	0.001 (0.001)	-0.001 (0.004)	-0.003 (0.002)
$\Sigma \Delta \Delta N_i / TA_i$	-0.194* (0.103)	-0.275*** (0.069)	-0.379*** (0.095)	-0.407*** (0.112)
$\Sigma \Delta \Delta S_i / TA_i$	-0.052 (0.077)	0.008 (0.035)	-0.018 (0.047)	-0.079** (0.033)
$\Sigma \Delta \Delta CF_i / TA_i$	-0.048 (0.090)	0.000 (0.045)	-0.495** (0.253)	-0.487** (0.235)
$\Sigma \Delta \Delta r$	-0.008 (0.009)	0.000 (0.002)	-0.007 (0.006)	0.003 (0.004)
Sargan test	64.57 (1.00)	52.02 (1.00)	42.54 (1.00)	39.76 (1.00)
m2 test	0.000 (1.00)	1.30 (0.20)	0.64 (0.53)	0.52 (0.60)

a. The m2 test for original regression equation showed that the residuals may be AR(2). I correct for this by using the same variables as the same instrument set, but each variable is lagged one further period. See Table 4 notes.

Figure 1:
The Effect of Cash Flow and Asymmetric Information on Investment
in the Povel and Raith Model

Appendix 2A: Variable Definitions

Variable	Description
GDP deflator	Implicit price index, all items. Statistics Canada, Cansim series label D15612.
Inventory Stock (N)	Compustat data on total inventories. Defined as merchandise bought for resale and materials and supplies purchased for use in production of revenue, including work in progress. Total nominal inventory stock converted to real terms using GDP deflator.
Inventory Investment (ΔN)	Calculated from nominal Compustat data on total inventory stocks deflated using the GDP deflator. Defined as change in real inventory stocks $N_{it} - N_{it-1}$.
Cash Flow (CF)	Compustat data defined as income before extraordinary items (income after all expenses except dividends) plus depreciation and amortization charges. Nominal cash flow is converted to real using the GDP deflator.
Sales (S)	Compustat data defined as sales net of cash discounts, trade discounts, returned sales and allowances. Nominal sales converted to real terms using GDP deflator.
Total Assets (TA)	Current assets plus net property, plant and equipment plus other non-current assets (including intangible assets, deferred items, investments and advances). Nominal values converted to real terms using GDP deflator.
Real Interest Rate (r)	Calculated as the prime lending rate less the inflation rate. Inflation rate is calculated using the GDP deflator. Prime interest rate data are from the Bank of Canada.

Chapter 3

Trade Credit and Credit Rationing

1. Introduction

This paper investigates trade credit supply and demand decisions with respect to credit constraints. I use financial statement data from a panel of Canadian firms to empirically test some of the implications of a model of trade credit and bank credit rationing developed by Burkart and Ellingsen (2003). This paper provides evidence of credit rationing by examining the substitution of trade credit for bank credit when finance constraints bind. The main finding is that firms with good investment prospects (defined as those with positive sales growth) but relatively low wealth use more trade credit as their access to bank credit declines. Trade credit use by the most profitable firms with positive sales growth does not depend on their bank credit levels during periods when finance constraints are expected to bind.

Trade credit refers to credit granted by a supplier to its customers. When the supplier does not require immediate payment, credit is effectively granted to the purchaser. The most common type of credit is simple net terms whereby full payment is required within a certain period after delivery, often 30 days. A more complicated form of trade credit involves two-part terms such that a discount is offered if payment is made within the discount period, or full payment is required at the end of the net period. Surveys by Ng, Smith and Smith (1999) and Dun and Bradstreet (1970) indicate that the most common two-part terms are 2/10 net 30. This means a two percent discount is available if the buyer pays within 10 days of

delivery, or the full amount is required if they pay 11 to 30 days after delivery. Two-part trade credit terms imply a very high effective annualized interest rate if the purchaser foregoes the discount, equal to 44.6% for 2/10 net 30 terms.¹⁷

Trade credit volume may be measured using accounts receivable (*AR*), and accounts payable (*AP*). Accounts receivable measures the unpaid claims a firm has against its customers at a given time, and therefore indicates its supply of trade credit. Accounts payable is a measure of demand for trade credit. Trade credit volumes are economically important; for example, in 1998 accounts receivable for non-financial firms in Canada totalled \$202.6 billion, and accounts payables were \$228.6 billion. These aggregate data show that accounts receivable were equivalent to about 13.4% of total sales revenue of \$1,511 billion in 1998, and the total accounts payable made up 15.1% of sales.¹⁸

The next section provides a review of the theoretical and empirical literature on trade credit. The third section describes a formal model of a firm's trade credit in the presence of credit rationing and the resulting testable hypotheses. Section four explains how the model is estimated. Section five describes the data and summary statistics. The estimation results for the reduced-form models of trade credit demand, supply and net trade credit are presented in section six. Section seven concludes.

2. Trade Credit Literature

Theories explaining why firms provide or use trade credit focus on several different motives. Broadly speaking, there are at least four important motives for supplying or

¹⁷ Assuming a 10 day discount period and 2% discount rate for a \$100 purchase, the full price can be viewed as the future value of a loan on the discounted amount for the remaining 20 day period. The implicit annualized interest rate can be found from the expression $98(1+i)^{365/20}=100$, which gives $i=0.446$.

¹⁸ Statistics Canada. *Financial and Taxation Statistics for Enterprises* 1998. Cat.61-219-XPB.p.74.

demanding trade credit: financial motives, transactions costs, product market information asymmetries, and price discrimination. Petersen and Rajan (1997) provide a good review of the theories of trade credit. The primary focus in this paper is on financial explanations of trade credit, however I briefly describe some of the alternative theories as well.

2.1 Financial Theories of Trade Credit

Financial factors are presented as a motive for both trade credit supply and demand. To explain why sellers supply trade credit, many theories assume a comparative advantage that suppliers have over financial institutions in supplying credit to certain segments of the market for short-term funds. One source of this advantage may be information asymmetries concerning the borrower's creditworthiness. When there are significant information asymmetries between lenders and borrowers, some potential borrowers may be credit-rationed by banks or other financial institutions.¹⁹

Petersen and Rajan (1997) explain that suppliers may have lower monitoring costs and are thus able to provide trade credit to firms that are bank-finance-constrained. Since suppliers observe the buyer at regular intervals, they may detect changes in the customer's financial health sooner than banks or other institutions. Furthermore, the supplier may be better able to enforce the credit contract with the threat of cutting off supplies. Another source of the supplier's comparative advantage may be their superior ability to salvage value from repossessed goods. The financing advantage suppliers may have allows them to provide liquidity to their customers. The supplier's role in providing liquidity was also

¹⁹ There is a relatively large literature on financing constraints and credit-rationing that arises due to information asymmetries in credit markets. See Hubbard (1998) for a review.

recognized in early models without asymmetric information by Emery (1984), Bitros (1979) and Schwartz (1974).

Smith (1987) shows that the terms of trade credit offered by the supplier effectively screen buyers in the presence of information asymmetries about credit worthiness. Buyers who choose not to pay in the discount period signal to the supplier that they are a greater credit risk and require additional monitoring.

Several recent papers formalize the relationship between bank credit rationing and trade credit due to information asymmetries. Jian (2001) provides a model of trade credit in which suppliers act as a second layer of financial intermediaries between banks and borrowers due to their lower monitoring costs. Biais and Gollier (1997) also emphasize the monitoring advantage of suppliers in a model where banks and suppliers have different signals about the borrower's credit worthiness. Trade credit helps alleviate the adverse selection problem for banks by identifying firms with good investment opportunities.

Burkart and Ellingsen (2003) argue that monitoring cost advantage does not fully explain the supplier's advantage over banks. They ask why would banks (specialists in evaluating credit worthiness) have less information than suppliers, and if they do, why do suppliers not use their superior information to lend cash rather than inputs? Burkart and Ellingsen develop a model in which trade credit suppliers can overcome the moral hazard problem of resource diversion by the borrower better than banks, because inputs are harder to divert than cash, and suppliers have a monitoring advantage with respect to input use only. Their model predicts that trade credit increases finance-constrained firms' access to bank credit, however the poorest firms will be constrained in both bank credit and trade credit. The Burkart and Ellingsen model is the basis for the empirical work here and it is

described in more detail in the next section.

Wilner (2000) examines trade credit relationships and the exploitation of market power. Large purchasers of inputs may use trade credit to exploit the trade creditors' dependence in cases of financial distress. In his model, large trade debtor firms can extract additional concessions from a dependent trade creditor in the case of financial distress, but they cannot do so with a trade creditor with less of a financial stake in future sales to the trade debtor. He predicts that large customers with dependent trade credit suppliers will prefer trade credit to bank credit if they are financially distressed.

2.2 Empirical Findings on Financial Motives for Trade Credit

Existing empirical work on financing models of trade credit supply is somewhat mixed. Nadiri (1969) finds empirical evidence that the amount of trade credit supplied is positively related to sales growth, and to improvements in the firm's own liquidity position. Mian and Smith (1992) show that bond-rated firms, which are assumed to have better access to low-cost financing, provide more trade credit than unrated firms do.

Petersen and Rajan (1997) use age and size as proxies for the suppliers' access to credit. They find evidence consistent with finance constraints in that older firms offer more trade credit than younger firms do, although the coefficients are not economically large. They do find a significant effect when size is used as a proxy for credit access; large firms offer significantly more trade credit than small firms do. However, small firms may not offer as much trade credit even if they also have ready access to funds from banks or other financial institutions due to economies of scale. Ng, Smith and Smith (1999) show that large firms may offer more trade credit because they experience scale economies in providing trade credit. After controlling for size, Ng, Smith and Smith do not find that liquidity is a

significant determinant in suppliers' decisions to offer trade credit. Demirguc-Kunt and Maksimovic (2001) compare manufacturing firms in 40 countries and find that the use of trade credit is a complement to bank credit, suggesting that suppliers do act as financial intermediaries between banks and borrowers.

One of the most surprising findings of Petersen and Rajan (1997) is that net profits are negatively related to the amount of trade credit offered, and that even distressed firms with low sales growth and negative profits offer trade credit. They suggest that this may be a matter of window dressing, in that firms in trouble attempt to keep the sales numbers up by offering trade credit to low quality customers. It has also been suggested that predatory behavior may also explain the provision of trade credit by distressed firms. If stronger firms bundle goods and credit together, weak firms may also have to offer both to compete.

Petersen and Rajan (1995, 1997) provide some evidence of finance constraints and trade credit demand using data on firms' relationships with their banks. Using the duration of the firm's relationship with its primary financial institution as an indicator of the degree to which a firm is credit rationed, they find firms with shorter banking relationships rely more on trade credit.

Nilsen (2002) argues that firms with reduced access to other sources of credit use trade credit as a poor substitute for other sources of financing. He finds evidence supporting this view of trade credit demand and shows that trade credit is particularly likely to be used as a substitute for other credit during periods of tight monetary policy.

2.3 Transactions Cost Motive

The transactions cost motive for using trade credit is the main focus of work by Ferris (1981) and Emery (1987). As a normal part of business activity, firms may face

uncertainty concerning the timing of revenues or expenses. Trade credit permits a decoupling of the delivery and payment, reducing the costs of transaction uncertainty and allowing firms to smooth revenues or payments. Ferris shows that trade credit can reduce transaction costs by reducing precautionary money holdings. Using industry level data, he finds that trade credit usage increases as the opportunity cost of holding money increases. Ferris also shows that the increased variability of money holdings and increased brokerage costs of moving between money and other assets lead to increased trade credit use, which implies a role for trade credit to reduce transaction costs.

2.4 Other Theories

Where there is uncertainty over the quality of the product, trade credit can also facilitate exchange. Smith (1987) shows that her signalling theory may also apply in these cases: the offer of trade credit may provide buyers with a quality guarantee. Firms without reputations in the goods market may be more likely to offer trade credit to give their customers time to inspect the goods before payment. Long *et al.* (1993) show that the more difficult it is for customers to assess product quality the higher is the likelihood of trade credit being offered. Petersen and Rajan (1997) do not find significant support for this theory. Ng, Smith and Smith (1999) argue that quality guarantees may be more likely when transactions are infrequent and buyers need to inspect the products before payment. They find weak evidence that sellers offer credit more when transactions are infrequent.

Brennan, Maksimovic and Zechner (1988) explain that the provision of trade credit may be a means of price discrimination. The supplier may effectively price discriminate between customers who are able to pay within the discount period and those that require the longer, net period to obtain the funds to pay. Those customers who pay early effectively

receive a lower price than those who require the full period to complete payment. If the customers who are able to pay within the discount period have elastic demand, the revenue to the supplier should increase by offering two part credit terms. Brennan, Maksimovic and Zechner's model also explains why credit may be offered at below market rates in cases such as automobile financing provided to consumers. Empirical work by Petersen and Rajan (1997) and Ng, Smith and Smith (1999) provide some evidence suggesting that trade credit is sometimes used as a price discrimination tool.

Theories of the firm may imply that the firm's decision to provide credit depends on the presence of relationship-specific investments and the potential for opportunism. Smith (1987) argues that if the supplier has made an investment in specific assets, it has an additional interest in the buyer's continued existence and it is more likely to supply trade credit. Petersen and Rajan (1997) find that suppliers offer credit to both profitable and unprofitable but growing firms, which suggests that trade credit is offered as an investment in particular trading relationships and supporting the future viability of their customers.

Although there is a sizable literature on trade credit, there has been very little analysis of trade credit data from Canada, especially for small firms. Since the financial systems in Canada differ from those of the United States, there may be differences in the provision or use of trade credit. Petersen and Rajan (1997) also point out that panel data analysis is required to further our knowledge of trade credit usage and its implications. To the best of my knowledge, this paper is one of the first studies using firm-level panel data to examine trade credit behaviour.

3. Theoretical Model Overview

Burkart and Ellingsen (2003) explain trade credit behaviour across firms and over the business cycle using a contract theory model. The key feature of Burkart and Ellingsen's model is the assumption that an entrepreneur or firm manager may divert some or all available resources for non-verifiable private benefits. The possibility of diversion creates a moral hazard problem in which suppliers have an information advantage over banks. This creates a role for trade credit in reducing the attractiveness of diversion relative to investment. As a result, firms of different wealth categories face different degrees of credit rationing and different trade credit usage patterns. The model provides the theoretical basis for the empirical analysis undertaken in this paper. The model is set up as follows.

3.1 Model Description

A wealth-maximizing, risk-neutral entrepreneur (or firm manager) with wealth $\omega \geq 0$ has access to an investment opportunity. The investment project converts input into output according to the production function $Q(I)$, where $I \leq q$ is the input quantity actually invested into the project, and q is the total quantity of inputs purchased. It is assumed that q is observable to the input supplier, but I is not observable to any outsiders. If there is opportunistic diversion by the entrepreneur, $I < q$. The entrepreneur is a price-taker in both the input and output markets. The input price is normalized to one and the output price is denoted p . Revenues equal pQ and are verifiable.

In a perfect credit market, with interest rate r_B , the entrepreneur would invest at the first-best investment level, $I = I^*(r_B)$. The entrepreneur's wealth cannot fund this investment level, since $\omega < I^*(r_B)$, so he needs to borrow. Since the entrepreneur may divert some resources for private gain, he cannot commit fully to investing in the project, and therefore

credit is rationed due to moral hazard. There are two sources of external funding, bank credit and trade credit. Banks and suppliers are assumed to operate in competitive markets, and they offer a loan contract to the entrepreneur simultaneously. The bank loan specifies the amount of bank credit, BC , and $D_b(pQ)$, the repayment obligations. Similarly, the supplier's trade credit loan contract includes: the amount of trade credit TC , the repayments $D_s(pQ)$, and input purchases q . Banks and suppliers are assumed to differ in their exposure to moral hazard. The suppliers have a monitoring advantage over the banks because even though neither the bank nor the supplier can contract directly on the investment level I , the supplier can condition its lending on input purchases, q . The limit on bank credit is a fixed amount $\overline{BC}$, but trade credit limit is a function of inputs purchased $\overline{TC}(q)$. The entrepreneur is assumed to borrow from no more than one bank and one supplier.

Creditor vulnerability is defined as the units of private benefit the entrepreneur gets from a unit of cash diverted, denoted $\varphi < 1$. Since inputs have to be converted to cash and then diverted, the private gain from diverting a unit of input is $\beta\varphi \leq \varphi$, $0 < \beta \leq 1$. The parameter β reflects the liquidity of the input; more liquid inputs have larger β and are more attractive for diversion.

The entrepreneur's problem, after accepting the contract offers from a bank and a supplier, is to choose q , BC , TC and I to maximize his utility, as shown in equation (1).

$$(1) \quad U = \max \{0, pQ(I) - BC - (1 + r_{TC})TC\} + \varphi [\beta(q - I) + (\omega + BC + TC - q)]$$

where r_{TC} is the interest rate on trade credit. U is maximized subject to the constraints:

$$q \leq \omega + BC + TC$$

$$I \leq q$$

$$BC \leq \overline{BC}$$

$$TC \leq \overline{TC}(q)$$

Note that the choice of I implies choosing to invest or to divert resources. The utility function's first term is the entrepreneur's residual return from investing the available resources, and the second term is his private benefit from diverting inputs and cash respectively. The first two constraints say that input purchases q are constrained to the total resources available and that investment is constrained by inputs purchased. The third and fourth constraints limit the entrepreneur's borrowing to his bank and trade credit limits.

The cost of trade credit funds, r_{TC} , is assumed to be greater than the cost of bank credit, so the entrepreneur uses trade credit only if the available cash from his own wealth and bank credit are less than the desired investment level at cost r_{TC} , that is, if $\omega + \overline{BC} < I^*(r_{TC})$. A non-diverting entrepreneur would use trade credit of amount TC^U which is just enough to invest to the desired level, or as much as his trade credit limit allows,

$$(2) \quad TC^U = \min \{ I^*(r_{TC}) - \overline{BC} - \omega, \overline{TC}(q) \}$$

However, the entrepreneur may divert cash or inputs. Burkart and Ellingsen show that the entrepreneur's equilibrium choice of investment or diversion is all-or-none because of the inefficiency of diversion technology compared to the certain investment return. The entrepreneur does not find it optimal to divert only part of the available funds. The authors then derive two incentive compatibility constraints to ensure that investment of the resources generates a private return to the entrepreneur that is greater than or equal to his private return from diversion, as shown in equations (3) and (4). Equation (3) ensures the

entrepreneur does not exhaust all available trade credit only to divert all inputs and remaining cash. Equation (4) is the incentive compatibility constraint required to prevent the entrepreneur from not purchasing any inputs at all and just diverting all the cash available from his own wealth and bank loans $(\overline{BC} + \omega)$.

$$(3) \quad pQ(\overline{BC} + TC^U + \omega) - \overline{BC} - (1 + r_{TC})TC^U = \phi\beta(\overline{BC} + \overline{TC} + \omega)$$

$$(4) \quad pQ(\overline{BC} + TC^U + \omega) - \overline{BC} - (1 + r_{TC})TC^U = \phi(\overline{BC} + \omega)$$

These constraints show that the entrepreneur is just indifferent between investing all available funds and diverting them.

The model generates several results with respect to borrowing and investment behaviour which are summarized in the top part of Table 1. First, it shows that entrepreneurs with high wealth will not use trade credit at all because they are not bank-credit-constrained. These firms invest at the first-best investment level subject to the bank credit interest rate $I^*(r_{BC})$. Second, firms with intermediate wealth will be bank-credit-rationed and will use trade credit to invest up to $I^*(r_{TC})$. Third, the poorest firms will be rationed in both bank credit and trade credit and will invest less than $I^*(r_{TC})$. Nevertheless, availability of trade credit results in more aggregate investment because entrepreneurs with medium or low wealth are able to invest more than if bank credit were the only source of financing.

3.2 Comparative Statics and Testable Predictions

By totally differentiating equations (3) and (4) with respect to parameters β , ω , ϕ , p and r_{TC} , Burkart and Ellingsen work out the effect of parameter changes on the equilibrium bank credit limit and trade credit limits, $\overline{BC}$ and $\overline{TC}$. From their comparative static results, I obtain the testable hypotheses which are summarized in the bottom portion of Table 1.

The bank credit and trade credit limits are affected symmetrically by changes in the parameters. The two credit limits move together for a given parameter change because the availability of trade credit makes investment of a given bank loan more profitable relative to diversion, and therefore raises the amount of credit that banks are willing to extend to the entrepreneur. The effects of a parameter change on the two credit limits reflect the returns to legitimate investment relative to the return to diverting resources. Increases in output price (p), and wealth (ω) increase $\overline{BC}$ and $\overline{TC}$ because a higher price raises the profitability of investment relative to diversion, and higher wealth facilitates repayment. Increases in creditor vulnerability (φ) makes diversion more attractive compared to investment, and therefore reduces both limits. Similarly, a higher trade credit interest rate (r_{TC}) also decreases the two credit limits because it reduces the payoff to investment relative to diversion. In the last column of Table 1 the predicted effects of parameter changes on trade credit usage by low-wealth follows this pattern exactly because those firms are at their trade credit limit. Finally, the low-wealth firms have a positive relationship between bank credit and trade credit because any change to one limit affects the availability of the other kind of credit. Thus for the poorest wealth firms, trade credit and bank credit are complements.

For the medium-wealth group, the predictions are more complex, as shown in the middle column of Table 1. These firms are at their bank credit limit, but they have not exhausted the trade credit available to them. Therefore, when a parameter change causes bank credit to decrease, they can compensate for the reduced bank credit by increasing their use of trade credit. So I get the main prediction that there will be a negative relationship between bank credit and trade credit for medium-wealth firms because they can substitute trade credit for bank credit. Burkart and Ellingsen also predict that medium-wealth firms

trade credit usage is decreasing in wealth and increasing in creditor vulnerability (since these variables both change $\overline{BC}$). The authors prove that liquidity does not affect how much trade credit the medium-wealth firms use. Changes in the product price or the cost of trade credit financing have an indeterminate effect because those parameters also affect the optimal investment level chosen, and there are two opposing effects.

The Burkart and Ellingsen model predicts that high-wealth entrepreneurs will not use trade credit because they are not bank-credit-rationed. So I do not expect there to be any significant relationships between trade credit usage and the other variables shown in the first column of Table 1.

Interpreting the business cycle as a shock to firms' wealth which reduces bank credit limits, I can see the effects of a negative shock to corporate wealth on trade credit behaviour by comparing the three wealth groups as follows:

- i. Unconstrained firms' trade credit use is uncorrelated with the business cycle;
- ii. Bank-credit-constrained firms that do not exhaust their trade credit limit will have countercyclical trade credit usage; and,
- iii. Bank-credit-constrained firms that exhaust their trade credit limit will have procyclical trade credit usage.

The Burkart and Ellingsen model focuses primarily on trade credit usage. With respect to a firm's decision to *offer* trade credit, Burkart and Ellingsen emphasize that invoices can be used as completely illiquid collateral to obtain further bank financing. Their model predicts that a firm that is constrained in the bank credit market will offer trade credit as long as the trade credit extended earns as high a return as their investment project.

4. Estimation Method

This section explains how I operationalize the predictions of the model summarized in Table 1. Bank credit rationing is believed to affect firms with good investment projects by preventing them from fully borrowing against their investment opportunities. I assume firms with good investment opportunities have positive sales growth. Therefore I first divide the sample into firms expected to be bank-credit-constrained or unconstrained, based on wealth categories where net income is the proxy for wealth. Net income is broader than profits but I use the terms interchangeably here. Detailed variable definitions and data descriptions are given in Appendix A.

We define the high-wealth, unconstrained firms as those having positive sales growth and net income after taxes greater than or equal to the 75th percentile value in the sample. The remaining credit-constrained firms should be divided according to wealth to identify those likely to be trade-credit-constrained as well. I define medium-wealth firms as those with positive sales growth and net income in the range of the 50th and 75th percentiles. The low-wealth firms are those with positive sales growth and net income less than the 50th percentile. Some of the low-profit firms actually have negative profits, but because they have positive sales growth I assume they have good investment opportunities. In the sample, the 50th and 75th percentile values for net income are \$29,000 and \$164,000 in 1997 Canadian dollars respectively.

We also analyze the trade credit behaviour of firms with negative sales growth and of distressed firms, defined as firms with both negative sales growth and negative profits. Although there is no explicit prediction of the trade credit behaviour for these types of firms

in the Burkart and Ellingsen model, earlier work in this thesis on inventory investment has shown that distressed firms' behaviour can have interesting and unexpected patterns.

Therefore I have five separate categories of firms reflecting the likelihood of credit constraints based on investment opportunities and wealth. A single firm may cross categories if its sales or profits change over the sample period.

4.1 Trade Credit Utilization (Accounts Payable)

The main predictions of the Burkart and Ellingsen model pertain to trade credit usage, which is commonly measured by accounts payable (*AP*). I estimate the model using a fixed effects linear regression model shown in equation (5).²⁰ The regression model is estimated separately for the five credit-constraint categories described above.

$$(5) \quad \frac{AP_{it}}{S_{it}} = \alpha + \beta_1 \frac{LOANS_{it}}{SALES_{it}} + \beta_2 \frac{CAPEX_{it}}{SALES_{it}} + \beta_3 \frac{PROFIT_{it}}{SALES_{it}} + \beta_4 COVRATIO_{it} + \beta_5 SALESSHOCK_{it} + u_i + e_{it}$$

The dependent variable is the ratio of accounts payable to sales (*AP/S*), the measure of trade credit used. Sales is used to scale all the non-ratio variables to control for possible nonstationarity and to control for heteroskedastic errors that may otherwise result from differences in the sizes of the firms. The regression includes: a constant and five main regressors plus a full set of year dummy variables (not shown), the firm-specific error term, u_i , and the idiosyncratic error term e_{it} .

²⁰ Fixed effects was chosen over the random effects panel data estimator based on the results of a Hausman test comparing the fixed and random effects coefficients. The chi-square test statistic comparing regressions on the overall sample was 89.03 with p -value 0.000, which means we reject the hypothesis of no significant difference in the random and fixed effect estimators. Since the fixed effects estimator permits covariance between firm-specific effects and the other regressors, which is likely the case with this data, we use fixed effects.

Bank loans are included in the regression to test if trade credit is a complement, a substitute, or is unrelated to bank financing. Thus the most important regressor is the firm's bank credit variable, *LOANS/SALES*. The coefficient of this variable is expected to be negative for medium-wealth firms and positive for low-wealth firms, and unrelated to trade credit for unconstrained (high-wealth) firms.

Capital expenditure (*CAPEX/SALES*) is intended to reflect the firm's decision to use inputs for investment purposes rather than for diversion, and therefore reflects the illiquidity of inputs purchased by the firm. A high level of investment in capital goods should correspond to a smaller likelihood of diversion by the firm. Firms investing heavily in capital equipment are also more likely to have firm-specific assets which are less liquid and harder to divert. Lower input liquidity is associated with higher bank and trade credit limits in the model, so I expect a positive coefficient on the capital expenditure variable for the low-wealth firms. There is no significant effect predicted for the medium or high-wealth firms. The capital expenditure variable is lagged one period since *AP* may be a component of current capital expenditures if the firm purchases capital items with trade credit.

An increase in the firm's wealth is expected to increase both its bank credit and trade credit limits; therefore I include the profit-to-sales ratio to measure the effect of changes in the firm's wealth on its trade credit usage. The model predicts that increased wealth will increase the trade credit limit and therefore, for firms that are constrained in the trade credit market, *PROFIT/SALES* should have a positive coefficient. For medium-wealth firms the coefficient should be negative.

The interest coverage ratio (*COVRATIO*) is a standard measure of credit quality and is included in the regression as a proxy for the creditor vulnerability parameter. A higher

coverage ratio improves the likelihood of repayment, and *reduces* creditor vulnerability. This variable is expected to decrease trade credit use by medium-wealth firms and increase trade credit use for low-wealth firms.

The *SALESSHOCK* variable controls for demand conditions faced by the firm, corresponding to output prices (p) in the theoretical model. Since I cannot observe a firm's output price or quantity, I need another measure to control for demand changes. The *SALESSHOCK* variable consists of the residuals from an auxiliary OLS regression of sales on a full set of industry and year dummy variables. The predictions from the auxiliary regression produces the expected sales for a firm in a given year and industry, and the residuals capture demand shocks faced by individual firms.

I do not have a measure of trade credit financing cost in the regression; however, Ng, Smith and Smith (1999) and others have observed that there is very little variation in trade credit terms over time.

In summary, I get a very simple pattern of sign predictions for the regression coefficients in the *AP* regressions. For the low-wealth firms, I expect that the regression variables will all have *positive* coefficients. For the medium-wealth firms, I expect all the variables will have *negative* coefficients except for *CAPEX/SALES*, which is expected to be zero, and the sign on *SALESSHOCK* is undetermined. For the high-wealth firms, all of the variables are expected to have coefficients of zero.

4.2 Trade Credit Supply (Accounts Receivable)

Burkart and Ellingsen argue that bank-credit-constrained firms will supply trade credit if it generates as high a return as other investments. Since firms with slow sales growth probably have fewer good investment opportunities than faster-growing firms, I compare

the responsiveness of accounts receivable of high-growth and low-growth firms that are likely to be finance constrained. The bank credit, wealth, illiquidity, creditor vulnerability, and demand variables should have the same effects for the trade credit offer amounts, since they reflect possible credit rationing by banks, and since the firm still faces a diversion decision – whether to divert bank credit or use it to finance accounts receivable (trade credit lending). So I simply add sales growth to the earlier regression to test whether firms with relatively better investment opportunities (high growth) extend less trade credit.

If the Burkart and Ellingsen model is correct, fast-growing firms should offer less trade credit because they have better investment opportunities, while slow-growing firms should offer more trade credit, since they have fewer good investment opportunities. Thus I expect that the growth variable will have a negative coefficient.

4.3 Net Trade Credit (Accounts Receivable – Accounts Payable)

Although the model does not explicitly deal with net trade credit, several existing studies have looked at the relationship between trade credit supplied and trade credit used. One can interpret the main theoretical results from Burkart and Ellingsen concerning the substitution or complementarity between bank and trade credit in terms of net trade credit as follows. Suppose that a firm faces a negative shock to its bank credit limit. The bank-credit constrained firms with medium-wealth should be able to increase their trade credit demand AP , to make up for the decrease in bank credit. At the same time, they may choose to decrease the trade credit they supply, AR , or perhaps for reasons of preserving good relationships with their customers, they keep their AR constant. Whether AR remains fixed or is decreased, net trade credit ($AR - AP$) will decrease as long as AP increases by more than

AR decreases. So for medium-wealth firms, I expect to see a significant positive coefficient on the bank loans variable in the net trade credit regression.

For low-wealth firms, bank loans reductions result in lower AP and may result in lower AR or no change in AR if the firm does not want to risk losing customers. Therefore net trade credit ($AR-AP$) for low-wealth firms increases if AR remains constant or is reduced by less than the reduction in AP . Alternatively, if AR and AP are reduced by the same amount in response to lower bank credit, then net trade credit is unchanged. Therefore, I expect that low-wealth firms' net trade credit is negatively related or unrelated to the bank credit variable. The model predicts that the unconstrained, high-wealth firms' trade credit decisions are unaffected so their net trade credit is not related to bank credit changes.

5. Data and Summary Statistics

We use annual firm-level data for the 11-year period 1988 to 1998. The data come from Statistics Canada's unpublished microdata files of the Financial and Taxation Statistics for Enterprises (FTSE) annual database. The FTSE is a detailed database of balance sheet, income statement and corporate income tax data. A key advantage of the FTSE microdata is that it includes both public and private firms, including some very small firms. Commercial databases often include only publicly-traded firms.

The sample contains 247,291 observations on 77,903 firms over the 11 year period from 1988 to 1998. Since some firms have fewer than 11 years of data, the panel is unbalanced. The aggregate FTSE data show that the total sales of goods and services by

Canadian non-financial firms was \$1,510 billion in 1998²¹. The sales by firms in the sample total \$978 billion in that year, so the sample accounts for about 64.7% of aggregate sales in 1998. Over the 11 years, the sample firms make up from 63.2% to 67.4% of the aggregate sales, so they appear to be representative of the Canadian non-financial sector as a whole. Appendix A describes in detail how the dataset is constructed.

Table 2 presents summary statistics for the variables used later in the regression models. Summary statistics are calculated for the full sample and also for the five different firm wealth categories used for the regression analysis as described above.

The summary statistics for most variables show the mean and median values are very different, indicating that the data are quite skewed. This reflects the fact that the population of Canadian firms consists of many small firms and a few large firms, but the large firms account for most of the total revenues and expenses. The sample's summary statistics reflect this distribution since the means are strongly influenced by the large firms, and are usually much higher than the median values. For instance, the mean of accounts payable is \$3.4 million but the median is only \$133 thousand. The mean accounts receivables are somewhat larger than accounts payable at \$3.86 million, but the median value is nearly identical to *AP* at \$132 thousand.

Scaling the variables by sales gives us the proportion of trade credit used or granted by the firm. The ratios appear to be less skewed since the medians and means are fairly similar for most variables. Across the different categories, the means and medians for accounts payable to sales (*AP/S*) ranges from 0.067 to 0.114. It is interesting that the high end of the range, 0.114, occurs in the distressed firms category which seems to indicate that

²¹ Statistics Canada. 1998. *Financial and Taxation Statistics for Enterprises* Cat. No.61-219XPB.

they are able to obtain some trade credit despite having negative sales growth and negative profits. The means and medians for accounts receivable to sales AR/S range from 0.068 to 0.135, with the highest proportion of AR/S occurring in the high profit group and the lowest AR/S median in the low profit group. The Canadian sample data here seem broadly consistent with Petersen and Rajan (1997) who use U.S. data from 1987 only. They calculate that the U.S. firms in their sample have average AP/S ratios of 0.044 for small firms and 0.116 for large firms; and they find an average AR/S of 0.073 for small firms, and 0.185 for large firms.

Net trade credit is small, with an overall average of \$460,000 and a median of just \$2,000. Most of the time it appears that firms keep AR and AP roughly equal since the mean and median values for net trade credit to sales ratios range from -0.001 to 0.018.

6. Estimation Results

The regression estimates for accounts payable to sales are presented in Tables 3 and 4. The first three columns show the unconstrained, constrained-medium-wealth and constrained-low-wealth categories of firms, where profit levels are the proxy for wealth. The final two columns present estimates for the negative sales growth firms and distressed firms. To test the model's main hypotheses concerning the relationship between bank credit and trade credit use, I compare the estimated coefficients on $LOANS/SALES$ across the five different regression models. To do so, I use the standard t-test for comparing means across different populations, where the means here are the coefficient estimates on the

LOANS/SALES variables.²² The differences in the coefficients and the t-ratios are shown in the bottom half of the regression tables.

6.1 Accounts Payable Estimates for Full Period 1988 to 1998

Table 3 summarizes the regression estimates for *AP/S* when data from the full period is used. The findings in Table 3 provide considerable support for Burkart and Ellingsen's predictions, especially for the low-wealth firms (column 3). These firms have a significant and positive relationship between bank and trade credit, and the other variables all have the expected positive coefficients. The results imply that low-wealth firms ability to use more trade credit is constrained by the amount of bank credit available to them. So there appears to be a complementary relationship between bank and trade credit for these firms.

The negative sales growth firms and distressed firms (columns 4 and 5) have coefficient estimates very similar to those of the low-wealth firms. They also appear to be constrained in both the bank credit and trade credit markets since the coefficients on *LOANS/SALES* of 0.028 and 0.023 indicate that there is a positive relationship between their bank loans and their use of trade credit.

For the medium-wealth firms (column 2), I find a negative relationship between bank credit and trade credit as predicted, but it is not statistically significant even at the 10% level. However, I also find that high-wealth, unconstrained firms' bank loans have a significant and positive effect on their trade credit usage when I expect no significant

²² The formula to calculate the t-ratios is: $t = \frac{b_1 - b_2}{s_p \sqrt{\frac{1}{n} + \frac{1}{m}}}$, where $s_p = \sqrt{\frac{(n-1)s_{b1} + (m-1)s_{b2}}{n+m-2}}$. In the

t-ratio equation, b_1 and b_2 are the coefficients on *LOANS/SALES* from the two different regression models being compared (shown as different columns) and s_{b1} and s_{b2} are their respective standard errors. The pooled standard error is denoted s_p and the number of observations in the two regressions are n and m .

relationship. Over the period 1988 to 1998, the wealthiest firms' AP/S do not appear to be independent of their bank credit usage, contrary to the model's predictions.

The t-tests comparing the coefficients on $LOANS/SALES$ all indicate that the coefficients are statistically different from each other.

Aside from the low-wealth firms, the coefficient signs for the other variables in Table 3 are not consistent with Burkart and Ellingsen's predictions. The wealth variable $PROFIT/SALES$ was positive and significant at the 1% level for all categories of firms, even though I expect its coefficient to have a negative sign for the medium-wealth firms and be insignificant for the high-wealth firms. All firms in the full sample period use significantly more trade credit as their profits increase. The business cycle can be seen as fluctuations in corporate wealth, this finding suggests that trade credit use in Canadian firms is procyclical. Burkart and Ellingsen hypothesize that if credit-rationed firms dominate among those that take trade credit, trade credit usage should be procyclical, but if unconstrained firms dominate, trade credit use will be counter-cyclical. Thus the findings here imply that most Canadian firms using trade credit faced some kind of credit rationing during this period.

6.2 Accounts Payable Estimates with Contractionary Monetary Policy 1989 to 1991

Some of the findings with respect to wealth changes and procyclical AP/S found in Table 3 may be affected by the time period of the full sample, 1988 to 1998. This period includes a long economic expansion in the middle-to-late 1990s. Since many of the firms in the unbalanced panel only enter the sample in this expansion I cannot be sure that I observe most firms when their credit constraints are binding.

In the late 1980s and early 1990s, Canada's monetary policy tightened as the central bank reduced inflation. From 1988 to 1989, the average annual real interest rate rose from

5.27% to 7.29%. Real interest rates were especially high in the period 1989 to 1991, averaging 7.95% per year over this period, compared to 5.47% for the other years in the sample. Assuming that 1989 to 1991 represents a period where credit limits are likely to bind, I estimate the *AP* model again using only these three years. The *AP/S* regression results for 1989 to 1991 are summarized in Table 4.

The findings in Table 4 present stronger evidence supporting Burkart and Ellingsen's predictions concerning the relationship between bank credit and trade credit. None of the variables (including bank loans) are significant for the high-wealth firms, as predicted by the model. For the medium-wealth firms, the coefficient on *LOANS/SALES* is negative and significant at the 5% level, indicating that they substitute trade credit for bank loans. However, the economic significance of this finding is relatively small. The average medium-wealth firm has *AP/S* of 8.9%, and *LOANS/SALES* of 7.0%. A one standard deviation increase in *LOANS/SALES* of 14.8% would only reduce *AP/S* to 8.1%, a decrease of 0.8%. The coefficients on the other variables in the *AP/S* regression for medium firms all have the expected signs, but only the wealth variable, *PROFIT/SALES*, is statistically significant. A positive shock to wealth decreases the medium-wealth firms' use of trade credit, as expected.

The *AP/S* regression results for the low-wealth firms over the tight money are mixed. *LOANS/SALES* has the expected positive sign but is not significant, and *PROFIT/SALES* has a negative and significant sign, contrary to the model. Since *LOANS/SALES* was significantly positive for low-wealth firms in the full sample period but is not significant here, it may be that the estimate is just imprecisely measured over the shorter period for this group. Another possible explanation is that the *a priori* categorizing of

low-wealth firms is too restrictive and a better category definition may include more of the firms with negative sales growth observations.

However, trade credit use is positively and significantly related to bank credit for the distressed firms and firms with declining sales in both Table 3 and 4, but the *LOANS/SALES* coefficient estimates during the 1989 to 1991 period are nearly double to those in regressions for 1988 to 1998. These firms only increase their trade credit use if bank credit increases, so these firms appear to be at both their bank credit and trade credit limits. The larger coefficients during the period of monetary tightening suggest that the link between bank credit and trade credit is tighter for declining and distressed firms during this period. The economic significance of the estimated coefficients on *LOANS/SALES* for the declining and depressed firms is also fairly small. An average firm with negative growth has *AP/S* of 10.5% and this would increase to 11.3% given a one standard deviation increase in *LOANS/SALES*. For depressed firms the corresponding change would be an increase in *AP/S* from 11.4% to 12.3%.

The findings from the accounts payable regressions generally support Burkart and Ellingsen's main predictions that as a firm's wealth declines, trade credit is substituted for bank credit by credit-rationed firms that have not exhausted their trade credit limits. If both credit limits are reached, bank credit and trade credit are complements rather than substitutes for the poorest firms. The most wealthy firms do not face credit-rationing and so their trade credit use is not related to their wealth or their use of bank credit in periods when one would expect credit constraints to bind.

6.3 Accounts Receivable Estimates

Tables 5 and 6 present estimates of the model for accounts receivable. The main test of the Burkart and Ellingsen model for AR/S is whether faster-growing firms provide less trade credit than slower-growing firms. This hypothesis is not supported by the data here since the coefficient on sales growth has a positive sign in nine of the ten regressions. So the sample firms usually increase trade credit relative to sales as sales growth increases. The only case where higher growth results in lower AR/S is for the declining growth firms over the full period. In the period of monetary tightening, negative sales growth firms also show a positive relationship between sales growth and trade credit offered. In all the regressions, however, the coefficients on the sales growth variable is economically small.

In all ten regressions, increases in bank credit correspond to significant increases in AR/S . As firms obtain more bank credit, they seem to pass on some of it to their credit-rationed customers via trade credit, consistent with most of the financing theories of trade credit and other empirical studies. What is surprising, however, is that the negative growth and distressed firms also appear to do so, although the $LOANS/SALES$ coefficients are significantly lower for the distressed firms compared to low-wealth firms (with positive growth) in both tables. Petersen and Rajan (1997) actually find something more extreme, namely that distressed firms offered proportionally more trade credit than other firms. One explanation may be the market power of customers of declining or distressed suppliers.

Wilner (2000) theorizes that dependent trade creditors are required by their large customers to provide credit in periods of financial distress. A financially distressed supplier may be distressed because its largest customers are distressed as well. Wilner predicts that large, financially distressed customers prefer trade credit from a dependent supplier to credit

from sources that are less dependent on the customer for future profits. The sample data here may be picking up on this kind of exploitation of market power predicted in his model and also found by Petersen and Rajan.

6.4 Net Trade Credit Estimates

It was argued earlier that the Burkart and Ellingsen model's hypotheses could be extended to generate testable predictions for net trade credit. Specifically, the bank credit variable is expected to have a positive influence on the net trade credit to sales ratio for medium-wealth firms, and to have a negative or zero coefficient for the low-wealth firms. The regression results provide mixed support for this prediction. The bank credit variable is positive and significant for all firm categories, not just medium-wealth firms; however, the coefficient on *LOANS/SALES* is significantly larger for the medium-wealth firms than for the low-wealth firms. This difference indicates that net trade credit is increased more in response to an increase in bank credit access for the medium-wealth firms than for the low-wealth firms that are also constrained in their access to trade credit.

7. Conclusions

Burkart and Ellingsen propose a model in which trade credit usage can be explained mainly as a solution to the moral hazard problem creditors face when lending to an entrepreneur or firm manager who may be able divert resources for private gain. They show that the possibility of diversion creates a role for trade credit to make bank credit more accessible since trade credit from the purchase of illiquid inputs makes investment more profitable relative to diversion. Three classes of firms exist in their model based on their wealth: unconstrained; bank-credit-constrained; and bank-credit and trade-credit-

constrained. Across the three classes, there are different interrelationships between bank credit and trade credit.

I find clear evidence of bank credit constraints for Canadian firms, based on the trade credit usage predictions of the Burkart and Ellingsen model. In periods when firms are likely to face credit constraints, high-wealth firms do not have to rely on trade credit to meet their investment needs because they have adequate access to other forms of credit. Therefore even in tight monetary conditions, the unconstrained firms' bank credit and trade credit levels are independent. However, less wealthy firms face bank-credit-rationing and they substitute trade credit for bank credit, especially during periods of contractionary monetary policy. The firms that are able to make this substitution are the medium-wealth firms who exhaust their bank credit limits, but not their trade credit limits. Firms with low wealth, negative profits and/or negative sales growth appear to be constrained in both bank and trade credit markets, and for them the two sources of credit are complements rather than substitutes.

The results here suggest that trade credit can play an important role in smoothing investment spending during periods of monetary contraction or recession because it allows at least the medium-wealth firms to continue to invest even when their access to bank credit is reduced.

Over the full period 1988 to 1998, increases in profit-to-sales ratios corresponded to an increase in the use of trade credit. So even as they became more profitable firms continued to use trade credit to meet their need for inputs, even though trade credit is less flexible and more costly than bank credit. This finding suggests that the majority of Canadian firms faced some degree of bank credit rationing over this period.

Trade credit supply increases as bank loans increase since all firms appear to offer their customers more credit if they can borrow more themselves. This was even the case for financially distressed firms with negative growth and negative profits. This may reflect exploitation of distressed firms' weak bilateral bargaining positions by their customers. Further research could explore distressed firms' trade credit behaviour in more detail. Contrary to the prediction of the Burkart and Ellingsen model, the provision of trade credit however, does not appear to increase significantly as sales growth declines. Net trade credit ($AR-AP$) increases for all five categories of firms as bank credit expands, rather than just for medium wealth firms.

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Table 1: Summary of Firm Behaviour and Testable Predictions of Trade Credit Usage in the Burkart and Ellingsen Model

	High Wealth	Medium Wealth	Low Wealth
Investment and Borrowing Behaviour:			
Bank Credit Usage	$BC < \overline{BC}$	$BC = \overline{BC}$	$BC = \overline{BC}$
Trade Credit Usage	$TC = 0$	$TC < \overline{TC}$	$TC = \overline{TC}$
Investment Level	$I = I^*(r_{BC})$	$I = I^*(r_{TC})$	$I < I^*(r_{TC})$
Predicted Change in Trade Credit Usage from an Increase in:			
Bank Credit (BC)	0	-	+
Liquidity (β)	0	0	-
Wealth (ω)	0	-	+
Creditor Vulnerability (φ)	0	+	-
Product Price (p)	0	?	+
Cost of Trade Credit Funds (r_{TC})	0	?	-

**Table 2: Summary Statistics for Full Sample and Different Wealth Categories
1988 - 1998, Thousands of 1997 Canadian Dollars**

	<u>All Observations</u>				<u>High Profit Firms</u>			
	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	N
Profit	1,126.39	29.77	27,249.71	247,291	8,304.93	783.00	46,961.15	30,723
Profit / Sales	5.809	1.605	431.690	247,291	11.851	4.909	130.874	30,723
Accounts Payable (AP)	3,400.70	133.00	33,127.55	247,291	12,559.16	1,568.00	70,409.78	30,723
AP / Sales	0.099	0.070	0.113	247,291	0.100	0.079	0.096	30,723
Sales	34,210.33	2,147.00	310,092.10	247,291	129,360.60	22,366.00	651,151.00	30,723
Accounts Receivable (AR)	3,860.65	132.00	36,948.31	247,291	14,904.50	2,317.00	81,168.10	30,723
AR / Sales	0.110	0.084	0.122	247,291	0.135	0.121	0.116	30,723
Net Trade Credit (AR - AP)	459.95	2.00	20,817.62	247,291	2,345.34	386.00	41,911.09	30,723
Net Trade Credit / Sales	0.011	0.003	0.133	247,291	0.035	0.028	0.121	30,723
Annual Sales Growth	253.55	3.10	44,066.54	153,767	378.34	14.47	18,111.63	30,723
Loans	4,144.83	64.68	56,946.72	247,291	11,636.37	543.12	79,754.82	30,723
Loans / Sales	0.099	0.012	0.188	247,291	0.079	0.007	0.165	30,723
Capital Expenditures	1,842.59	23.35	26,139.91	247,291	7,556.65	348.05	58,336.64	30,723
Capital Expenditures / Sales	0.041	0.009	0.080	247,291	0.049	0.018	0.082	30,723
Coverage Ratio	17.89	2.17	271.28	194,856	68.03	5.87	536.92	24,781

Nominal dollar values converted to 1997 dollars using the GDP deflator.

Table 2: Summary Statistics for Full Sample and Different Wealth Categories (cont.)
1988 - 1998, Thousands of 1997 Canadian Dollars

	Medium Profit Firms				Low Profit Firms			
	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	N
Profit	90.26	85.55	41.31	23,996	-1,833.46	-7.54	43,893.53	34,916
Profit / Sales	6.889	3.357	14.447	23,996	-5.65	-0.44	127.57	34,916
Accounts Payable (AP)	606.68	162.00	2,867.89	23,996	3,200.62	90.00	32,816.37	34,916
AP / Sales	0.089	0.067	0.091	23,996	0.097	0.067	0.111	34,916
Sales	7,305.46	2,475.00	26,023.10	23,996	28,998.18	1,633.50	255,996.50	34,916
Accounts Receivable (AR)	699.62	185.00	2,839.31	23,996	3,046.79	74.00	24,186.47	34,916
AR / Sales	0.107	0.088	0.108	23,996	0.096	0.068	0.111	34,916
Net Trade Credit (AR - AP)	92.94	17.00	1,638.27	23,996	-153.83	0.00	18,544.44	34,916
Net Trade Credit / Sales	0.018	0.011	0.113	23,996	0.000	0.000	0.126	34,916
Annual Sales Growth (%)	56.19	13.62	1,201.30	23,996	777.99	11.06	90,894.93	34,916
Loans	615.92	79.06	2,959.83	23,996	5,949.85	68.28	100,309.60	34,916
Loans / Sales	0.070	0.010	0.148	23,996	0.106	0.017	0.193	34,916
Capital Expenditures	169.29	31.83	881.06	23,996	1,382.81	15.03	19,928.22	34,916
Capital Expenditures / Sales	0.039	0.011	0.074	23,996	0.038	0.008	0.076	34,916
Coverage Ratio	15.90	4.71	29.81	19,931	-6.51	0.70	185.56	27,893

Table 2: Summary Statistics for Full Sample and Different Wealth Categories (cont.)
1988 - 1998, Thousands of 1997 Canadian Dollars

	Negative Growth Firms				Distressed Firms			
	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	N
Profit	582.59	7.63	23,039.42	63,261	-2,085.46	-71.68	21,638.75	25,926
Profit / Sales	4.90	0.51	598.75	63,261	-15.06	-4.31	86.34	25,926
Accounts Payable (AP)	3,618.53	145.00	31,994.01	63,261	3,134.45	117.00	25,512.33	25,926
AP / Sales	0.105	0.071	0.123	63,261	0.114	0.076	0.136	25,926
Sales	35,685.75	2,383.00	322,624.60	63,261	27,794.90	1,859.00	235,763.20	25,926
Accounts Receivable (AR)	4,119.52	145.00	39,316.64	63,261	3,168.26	100.00	25,242.85	25,926
AR / Sales	0.115	0.086	0.130	63,261	0.113	0.080	0.132	25,926
Net Trade Credit (AR - AP)	500.99	2.00	23,915.04	63,261	33.81	0.00	12,919.69	25,926
Net Trade Credit / Sales	0.011	0.003	0.144	63,261	-0.001	0.000	0.152	25,926
Annual Sales Growth	-18.17	-11.60	19.02	63,261	-20.79	-14.35	19.91	25,926
Loans from Non-Affiliates	4,596.70	63.66	52,815.90	63,261	5,093.72	100.90	37,754.28	25,926
Loans	0.102	0.011	0.194	63,261	0.122	0.017	0.215	25,926
Capital Expenditures	1,866.64	16.43	23,594.33	63,261	1,419.73	10.78	20,215.45	25,926
Capital Expenditures / Sales	0.034	0.006	0.071	63,261	0.032	0.005	0.070	25,926
Coverage Ratio	10.64	1.29	223.42	49,768	-13.88	-1.11	232.64	21,269

Table 3: Accounts Payable Regressions, Full Sample Period, 1988-1998
Fixed Effects Regressions with Net Profit Used to Define Wealth Categories

Dep. Variable is AP / Sales	(1) Growth > 0 High Wealth	(2) Growth > 0 Med. Wealth	(3) Growth > 0 Low Wealth	(4) Growth < 0	(5) Distressed
Loans / Sales	-0.012 (-2.55)**	-0.010 (1.43)	0.013 (2.51)**	0.028 (6.69)***	0.023 (3.06)***
(Capital Exp. / Sales) (t-1)	0.003 (1.35)	0.000 (0.05)	0.000 (0.72)	0.008 (1.33)	-0.004 (0.32)
Profit / Sales	0.000 (3.81)***	0.001 (4.47)***	0.000 (4.05)***	0.000 (3.87)***	0.000 (10.88)***
Coverage Ratio	0.000 (2.87)***	0.000 (0.02)	0.000 (6.84)***	0.000 (0.92)	0.000 (0.38)
Sales Shock	0.000 (5.14)***	0.000 (0.59)	0.000 (3.04)***	0.000 (4.37)***	0.000 (5.29)***

T-Tests of Difference in the Loans/Sales Coefficients Across Firm Wealth Categories:

High Wealth - Med. Wealth	-0.002 (-26.92)				
Med. Wealth - Low Wealth		-0.023 (-317.38)			
Low Wealth - Neg. Growth			-0.015 (-315.73)		
Low Wealth - Distressed				-0.010 (-131.13)	

R-squared	0.009	0.010	0.017	0.016	0.041
Observations	24461	19770	27492	49648	21216
Number of Firms	10647	11688	16253	24354	13196

Value of t-statistics in parentheses. All the regressions also include a constant and year dummy variables. The High Wealth category is defined as firms with net profit greater than the 75th percentile in the sample. Medium Wealth firms have net profits between the median and 75th percentile values. Low Wealth firms have net profits below the median. Distressed firms are firms with negative profit and negative sales growth.

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

Table 4: Accounts Payable with Contractionary Monetary Policy, 1989-1991
Fixed Effects Regressions with Net Profit as a Proxy for Wealth Categories

Dep. Variable is AP / Sales	(1) Growth > 0 High Wealth	(2) Growth > 0 Med. Wealth	(3) Growth > 0 Low Wealth	(4) Growth < 0	(5) Distressed
Loans / Sales	-0.009 (0.65)	-0.052 (-2.17)**	0.008 (0.64)	0.045 (4.43)***	0.041 (2.25)**
(Capital Exp. / Sales) (t-1)	0.007 (1.45)	-0.002 (0.74)	0.001 (0.36)	-0.029 (-2.46)**	-0.065 (-3.10)***
Profit / Sales	0.000 (0.44)	-0.002 (-3.90)***	-0.001 (-8.28)***	0.000 (2.33)**	0.000 (1.67)*
Coverage Ratio	0.000 (0.18)	0.000 (1.14)	0.000 (0.20)	0.000 (0.33)	0.000 (0.10)
Sales Shock	0.000 (0.40)	0.000 (0.70)	0.000 (0.72)	0.000 (3.48)***	0.000 (1.47)

T-Tests of Difference in the Loans/Sales Coefficients Across Firm Wealth Categories:

High Wealth - Med. Wealth	0.044 (127.78)				
Med.Wealth - Low Wealth			-0.061 (-186.38)		
Low Wealth - Neg. Growth				-0.036 (-236.58)	
Low Wealth - Distressed					-0.033 (-126.67)

R-squared	0.003	0.029	0.059	0.031	0.046
Observations	6809	5545	7780	16776	7316
Number of Firms	4976	4450	6203	11995	5806

See note to Table 3.

Table 5: Accounts Receivable Regressions, Full Sample Period, 1988-1998
Fixed Effects Regressions with Net Profit Used to Define Wealth Categories

Dep. Variable is AR / Sales	(1) Growth > 0 High Wealth	(2) Growth > 0 Med. Wealth	(3) Growth > 0 Low Wealth	(4) Growth < 0	(5) Distressed
Loans / Sales	0.036 (7.52)***	0.059 (7.97)***	0.071 (14.77)***	0.045 (11.19)***	0.041 (6.32)***
(Capital Exp. / Sales) (t-1)	0.030 (3.42)***	0.022 (2.22)**	0.015 (1.66)*	0.018 (2.04)**	0.031 (1.82)*
Sales Growth	0.000 (7.05)***	0.000 (0.27)	0.000 (0.46)	-0.001 (-20.07)***	0.000 (7.82)***
Profit / Sales	0.000 (1.12)	0.001 (5.04)***	0.000 (1.70)*	0.000 (1.42)	0.000 (0.88)
Coverage Ratio	0.000 (6.13)***	0.000 (1.39)	0.000 (3.19)***	0.000 (2.43)**	0.000 (2.25)**
Sales Shock	0.000 (1.42)	0.000 (0.67)	0.000 (8.81)***	0.000 (0.92)	0.000 (0.81)
T-Tests of Difference in the Loans/Sales Coefficients Across Firm Wealth Categories:					
High Wealth – Med. Wealth		-0.023 (-271.93)			
Med.Wealth – Low Wealth			-0.012 (-157.85)		
Low Wealth – Neg. Growth				0.026 (595.55)	
Low Wealth – Distressed					0.004 (60.81)
R-squared	0.014	0.018	0.031	0.029	0.021
Observations	24781	19931	27893	49768	21269
Number of Firms	10809	11806	16485	24421	13234

See note to Table 3.

Table 6: Accounts Receivable with Contractionary Monetary Policy, 1989-1991
Fixed Effects Regressions with Net Profit as a Proxy for Wealth Categories

Dep. Variable is AR / Sales	(1) Growth > 0 High Wealth	(2) Growth > 0 Med. Wealth	(3) Growth > 0 Low Wealth	(4) Growth < 0	(5) Distressed
Loans / Sales	0.072 (5.01)***	0.073 (3.22)***	0.064 (5.14)***	0.076 (7.22)***	0.032 (1.98)**
(Capital Exp. / Sales) (t-1)	0.030 (1.35)	-0.009 (0.43)	0.009 (0.49)	0.052 (2.64)***	0.060 (1.73)*
Sales Growth	0.000 (7.47)***	0.000 (0.59)	0.000 (0.36)	0.000 (6.52)***	0.000 (1.57)
Profit / Sales	0.000 (0.57)	0.000 (0.73)	0.000 (0.98)	0.000 (0.12)	0.000 (1.16)
Coverage Ratio	0.000 (0.01)	0.000 (0.96)	0.000 (1.05)	0.000 (2.57)**	0.000 (0.45)
Sales Shock	0.000 (0.43)	0.000 (0.74)	0.000 (0.38)	0.000 (1.12)	0.000 (0.06)

T-Tests of Difference in the Loans/Sales Coefficients Across Firm Wealth Categories:

High Wealth - Med. Wealth	-0.001 (-1.87)				
Med.Wealth - Low Wealth			0.009 (26.00)		
Low Wealth - Neg. Growth				-0.012 (-69.51)	
Low Wealth - Distressed					0.045 (172.38)

R-squared	0.048	0.014	0.023	0.041	0.013
Observations	6903	5593	7904	16807	7325
Number of Firms	5054	4494	6308	12025	5815

See note to Table 3.

Table 7: Net Trade Credit (AR - AP) Regressions, Full Sample Period, 1988-1998
Fixed Effects Regressions with Net Profit Used to Define Wealth Categories

Dep. Variable is Net TC / Sales	(1) Growth > 0 High Wealth	(2) Growth > 0 Med. Wealth	(3) Growth > 0 Low Wealth	(4) Growth < 0	(5) Distressed
Loans / Sales	0.048 (8.46)***	0.070 (8.31)***	0.053 (8.77)***	0.029 (6.04)***	0.031 (3.69)***
(Capital Exp. / Sales) (t-1)	-0.046 (-4.46)***	-0.046 (-4.14)***	-0.042 (-3.73)***	-0.079 (-7.55)***	-0.090 (-4.16)***
Sales Growth	0.000 (1.19)	0.000 (0.02)	0.000 (0.40)	0.000 (5.86)***	0.000 (4.61)***
Profit / Sales	0.000 (8.94)***	0.000 (0.53)	0.000 (3.35)***	0.000 (2.51)**	0.000 (7.20)***
Coverage Ratio	0.000 (1.12)	0.000 (0.39)	0.000 (0.13)	0.000 (0.62)	0.000 (1.64)
Sales Shock	0.000 (1.22)	0.000 (0.62)	0.000 (1.16)	0.000 (1.34)	0.000 (0.16)
T-Tests of Difference in the Loans/Sales Coefficients Across Firm Wealth Categories:					
High Wealth - Med. Wealth		-0.023 (-251.76)			
Med. Wealth - Low Wealth			0.017 (241.54)		
Low Wealth - Neg. Growth				0.024 (395.23)	
Low Wealth - Distressed					-0.002 (-22.33)
R-squared	0.013	0.012	0.011	0.007	0.025
Observations	24781	19931	27893	49768	21269
Number of Firms	10809	11806	16485	24421	13234

See note to Table 3.

Table 8: Net Trade Credit with Contractionary Monetary Policy, 1989-1991
Fixed Effects Regressions with Net Profit as a Proxy for Wealth Categories

Dep. Variable is Net TC / Sales	(1) Growth > 0 High Wealth	(2) Growth > 0 Med. Wealth	(3) Growth > 0 Low Wealth	(4) Growth < 0	(5) Distressed
Loans / Sales	0.086 (5.15)***	0.130 (4.36)***	0.042 (2.81)***	0.044 (3.64)***	0.007 (0.31)
(Capital Exp. / Sales) (t-1)	-0.027 (1.03)	-0.056 (-2.14)**	-0.045 (-2.00)**	-0.063 (-2.79)***	-0.144 (-3.11)***
Sales Growth	0.000 (1.29)	0.000 (1.00)	0.000 (0.45)	0.000 (2.03)**	0.001 (4.29)***
Profit / Sales	0.000 (0.33)	0.002 (3.88)***	0.000 (5.03)***	0.000 (1.38)	0.000 (0.08)
Coverage Ratio	0.000 (0.32)	0.000 (1.31)	0.000 (0.58)	0.000 (0.02)	0.000 (0.38)
Sales Shock	0.000 (0.53)	0.000 (1.53)	0.000 (0.44)	0.000 (0.43)	0.000 (0.51)
T-Tests of Difference in the Loans/Sales Coefficients Across Firm Wealth Categories:					
High Wealth - Med. Wealth		-0.044 (-90.66)			
Med. Wealth - Low Wealth			0.087 (199.79)		
Low Wealth - Neg. Growth				-0.002 (-8.80)	
Low Wealth - Distressed					0.038 (112.60)
R-squared	0.017	0.042	0.025	0.007	0.033
Observations	6903	5593	7904	16807	7325
Number of Firms	5054	4494	6308	12025	5815

See note to Table 3.

Appendix 3A: Variable Definitions and Data Description

Variable	Description
Accounts Payable (AP)	Accounts Payable from Trade (arising from sale of goods and services) measured in 1997 Canadian dollars. Nominal values converted to real using the GDP deflator.
Accounts Receivable (AR)	Accounts Receivable from Trade (arising from purchase of goods and services), measured in 1997 Canadian dollars.
Net Trade Credit	AR - AP
Sales	Sales of goods and services in 1997 dollars.
Profit	Net Income after all items have been included (taxes, income from affiliates, extraordinary items etc.), measured in 1997 dollars.
Loans	Loans from Non-Affiliates in 1997 dollars.
Capital Expenditure	Net Capital Expenditures, measured in 1997 dollars.
Coverage Ratio (COVRATIO)	Earnings Before Interest and Taxes (EBIT) / Interest Expense on Debt, where EBIT is calculated as Net Profit Before Tax + Interest Expense on Debt
Growth	Percentage change in sales from previous year.
Sales Shock	Residual from auxiliary OLS regression of sales on a constant and year dummies and industry dummy variables.

Description

The data come from Statistics Canada's unpublished microdata files of the Financial and Taxation Statistics for Enterprises (FTSE) annual database. The FTSE is a detailed database of balance sheet, income statement and corporate income tax data. A key advantage of the FTSE microdata file is that it includes both public and private firms, including some very small firms. Commercial databases often include only publicly-traded firms.

The dataset contains enterprise-level data that are collected using a combination of survey data and administrative data from corporate tax returns provided to Statistics Canada from Canada Customs and Revenue Agency (CCRA). The sample is stratified three ways: by

industry, by country of control, and by size. Industries are defined using 63 groupings of the 1980 2-digit SICs.²³ Within each industry there are three strata based on whether the firm's country of control is Canada, the United States or another country. Finally, within the country of control stratum, there are multiple size categories based on the firm's assets or revenues. The largest firms in each industry are sampled with certainty, although the size bounds vary by industry. For most industries this "take-all" stratum consists of the largest firms with assets or annual revenues of more than \$25 million in current dollars. The second "take-some" strata consists of smaller firms that are randomly selected for inclusion in the survey. In the take-some stratum, data were collected through a mix of surveys and administrative tax files. The final stratum of the sample consists of the smallest firms which were not surveyed, so all their data come from the tax return files.

We select only the non-financial firms from the dataset. Industries included in the non-financial sector are listed in Appendix B. I also remove observations from the sample if regression variables seem to have very extreme values. Specifically I restrict the sample to those observations where the dependent variables in the regressions, the accounts payable to sales and accounts receivable to sales ratios, were between zero and one; this removes approximately 1% of the original observations. Observations where sales are negative are also omitted, as are the cases where ratios of capital expenditures to sales or bank loans to sales were zero or greater than the 95th percentile value.

²³ This survey used a non-standard SIC system called SIC-C 14. This refers to the Canadian SIC for Companies and Enterprises and it is intended to categorize companies based on their activities.

Appendix 3B: Non-Financial Industry Groups

SICC 1980 Class 14 Grouping	Description
Specialized Manufacturing:	
14	Food processing
15	Brewed, distilled and fermented beverages manufacturing
16	Tobacco processing (incl. Farming)
17	Footwear manufacturing
18	Primary textiles and textile products manufacturing
19	Clothing and other apparel manufacturing
20	Wood products manufacturing
21	Pulp and paper, and other paper products manufacturing
22	Printing and publishing
23	Primary metal products manufacturing
24	Non-ferrous metals manufacturing (except aluminum)
25	Fabricated metal products manufacturing
26	Transportation equipment manufacturing
27	Electrical products manufacturing
28	Electronic products manufacturing
29	Cement, concrete and concrete products manufacturing
30	Chemicals and other chemical products manufacturing
31	Scientific and professional apparatus manufacturing
32	Primary steel products, integrated operations
33	Motor vehicle parts and accessories manufacturing
34	Paper boxes and bags (incl. plastic bags) manufacturing
35	Plastic and rubber manufacturing
36	Commercial and institutional furniture and equipment manufacturing
37	Prefabricated and pre-engineered buildings manufacturing
38	Other consumer goods manufacturing n.e.c.
Storage:	
47	Storage and warehousing
Wholesale Trade:	
54	Livestock and raw milk wholesaling
55	Other food products wholesaling
56	Agricultural supplies and products wholesaling
57	Tobacco products wholesaling
58	Apparel and footwear wholesaling
59	Household appliances wholesaling
60	Motor vehicles and motor vehicle parts and accessories; trucks and buses; auto mobile recyclers wholesaling
61	Recreational vehicles and other transportation equipment wholesaling
62	Forest products and lumber wholesaling
63	Paper and paper products wholesaling
64	Other metals and metal products wholesaling
65	Building materials wholesaling
66	Electrical machinery, equipment and supplies wholesaling
67	Electronic equipment wholesaling
68	Drugs, toiletries and industrial and household chemical products wholesaling
69	Textiles, textile and related products wholesaling
70	Books, magazines and periodicals wholesaling
71	Other consumer goods wholesaling n.e.c.
Retail Trade:	
72	Food retailing
73	Drugs, patent medicines and toiletries retailing
74	Clothing and shoes retailing

75	Motor vehicle dealers and repair shops
76	Recreational vehicle dealers
77	Service stations
78	Department stores
79	Hardware, home and auto supplies retailing
80	Sporting goods, jewellery and non-store retailing

Mining and Manufacturing:

115	Non-metallic minerals and mineral products and industrial organic chemicals mining and manufacturing
116	Mining, smelting and refining of non-ferrous metals (except aluminum and uranium)
117	Uranium mining and refining
118	Asbestos and other building materials mining and manufacturing

Mining, Manufacturing, Transportation, Wholesaling, and Services:

119	Petroleum exploration, production, refining and marketing
120	Trucking and other services incidental to petroleum and natural gas
121	Coal mining and distributing, and other fuels production and distribution, n.e.c.

Manufacturing and Wholesaling:

122	Motor vehicles, motor vehicle parts and accessories manufacturing and wholesaling
123	Household furniture manufacturing and wholesaling
124	Meat, poultry, milk, bakery products and animal feeds manufacturing and wholesaling
125	Agricultural machinery and equipment manufacturing and wholesaling
126	Soft drinks manufacturing and wholesaling
127	Petroleum refining and distributing
128	Aluminum and aluminum products manufacturing and wholesaling
129	Leather and allied products manufacturing and wholesaling (except footwear)
130	Computer equipment and related services manufacturing and wholesaling
131	Industrial, construction, mining machinery and equipment manufacturing and wholesaling
132	Tires and tubes, integrated operations
133	Truck and bus bodies and commercial trailers manufacturing and wholesaling
134	Household appliances manufacturing and wholesaling
135	Other consumer goods manufacturing and wholesaling

Manufacturing and Services:

136	Metal heating equipment and plumbing fixtures, fabricated metal products and machine and welding shops manufacturing services
137	Commercial printing and duplicating services
138	Outdoor displays and other advertising services

Transportation, Storage, Utilities and Services:

142	Cereal grain and oil seed storage and handling
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Wholesaling and Services:

143	Commercial, professional and institutional furniture, machinery, and equipment
144	Agriculture, mining, construction and industrial equipment wholesaling, renting, and leasing
145	Computer and peripheral equipment sales and services

Retailing and Services:

146	Household furniture, appliances, and furnishings retailing, renting and leasing
147	Other general merchandise retailing and services
148	Other specialty merchandise retailing, renting and repairing

Retailing and Wholesaling:

149	Liquor, beer and wine wholesaling and retailing
150	Tires and batteries wholesaling and retailing

Chapter 4

Investment, Private Information and Social Learning: A Case Study of the Semiconductor Industry

1. Introduction

This paper tests the implications of a model of social learning and capital investment. Aggregate investment has historically been one of the most volatile components of GDP over the business cycle. Despite its prominence, the reasons for the volatility in investment spending are not well understood. Several empirical studies find that standard neoclassical models of investment, including q theory, do not explain a large portion of the variation in investment. Several potential explanations for the poor empirical performance of investment models have been proposed, including: finance constraints; irreversibility of investment; measurement error in q , aggregation over heterogeneous investment goods; and the lumpiness of investment spending at the firm level. Caballero (1999) provides a survey and references.

Social learning theories of investment provide an alternative view by focusing on how markets aggregate disparate private information as agents learn from each other. These models can generate abrupt changes in aggregate investment, consistent with the stylized facts. Social learning models also show that problems in information aggregation may lead to socially inefficient delays in investment activity. Social learning theories feature uncertainty about an important state variable, like demand, combined with the possibility that useful information is created when other agents act. Caplin and Leahy (1994) (CL94) develop a model in which firms decide to continue or suspend an investment project based on their own private information and their reaction to others' actions. Their model explains why

investment can suddenly collapse and therefore may be useful in understanding the empirical patterns in investment spending as the business cycle turns from expansion to recession.

Empirical tests of social learning models of investment so far have been rare. This paper provides some of the first empirical tests of social learning using capital investment data. I test the main social learning result from CL94 that, other things being equal, suspensions by other firms make it more likely that a given firm will suspend its investment. I use a unique dataset of 258 semiconductor fabrication plants with investment projects underway in the period 1995 to 2002. In general, the decision of one semiconductor plant to suspend an investment does not appear to depend on the actions of others when the firm is investing in standard technology. However, when adopting a significant new technology, other plants' suspensions had a significant influence on the probability of suspending one's own project. This finding suggests social learning is more important when agents face a decision about technology adoption, but may not be an important factor in explaining more conventional investment decisions.

2. Related Literature

Caplin and Leahy (1994) build an (S,s)-type model of irreversible investment in which fixed adjustment costs lead firms to adjust their behaviour infrequently, choosing when to switch from inertia to action (suspending their investment project).²⁴ CL94 add private information to the model, creating the possibility for social learning from other agents' suspensions. Project suspensions cause previously disparate, heterogeneous, private

²⁴ Related (S,s) papers include : Blinder (1981), Caplin (1985), Caplin and Spulber (1987), Cabellero and Engel (1991) and Caplin and Leahy (1993).

information to be aggregated by the market, and may lead to significant changes in overall beliefs and, potentially, a collapse in investment.

Several early models of irreversible investment with uncertainty and learning, such as Zeira (1987, 1994), Demers (1991), Rob (1991) and Caplin and Leahy (1993), assume all agents have the same information. These models tend to generate gradual changes as agents learn from the outcomes of earlier investments. In contrast, CL94 features heterogeneous beliefs and generates discontinuous investment patterns whereby industry investment can collapse suddenly after the first suspensions as other agents learn that demand is low.

In the CL94 model, investment suspensions in the low-demand state are delayed longer than they would be in a full-information-sharing equilibrium. The delay occurs because, rather than acting independently, firms may wait to see if other firms suspend. Resources can be wasted by continuing projects when demand is low, resulting in lower social welfare than if the suspensions had occurred earlier. Gale (1996) reviews many social learning theories of investment and shows that the prediction of socially inefficient delays is robust to a broad range of assumptions used in social learning models.

Several social learning models, including Romer (1993), Bulow and Klemperer (1994), and Chamley and Gale (1994), allow heterogeneity but take the differences in beliefs as given, whereas Caplin and Leahy allow agents' beliefs to evolve. More similar to CL94 are the early theories of information cascades developed first by Banerjee (1992), Bikhchandani et al (1992), Lee (1992) and Welch (1992). These papers also focus on the aggregation of dispersed private information and social learning, which can lead to dramatic changes in beliefs. The key difference is that CL endogenize the timing of the action that leads to the information cascade, whereas the other models impose an exogenous order on the timing of agents' decisions.

Recent social learning investment models include Caplin and Leahy (1998) and Hovarth et al (2001). CL98 uses a search framework to consider information aggregation and endogenous timing in the context of the decision whether to enter a property market with uncertain demand. This model also generates socially inefficient delay and a discontinuous pattern of activity. CL98 concludes that their model fits the observed behaviour of the 1990s retail property boom in New York better than the alternative explanation of crowd externalities. Hovarth et al (2001) develop a model of social learning and firm entry and exit, similar to CL94. Their model can generate either discontinuous or gradual patterns of entry, depending on the assumptions about how uncertainty is resolved. They find the predictions of their model are consistent with the observed empirical patterns of mass entry and exit in the beer, automotive and tire industries in the U.S. in the late 19th and early 20th centuries.

Empirical Literature

Brock and Durlauf (2001) discuss some applications of social learning models, and examine the main econometric problems involved in estimating them. So far, empirical studies of social learning have usually focused on individual behaviour. Few authors test social learning theories empirically with data on firms.²⁵ Although social learning models often examine investment decisions, I present some of the first empirical studies of social learning and capital investment behaviour.

Most closely related to the work here are two recent studies of technology adoption and social learning by Foster and Rosenzweig (1995), and Munshi (2003). They test for social

²⁵ The literature on social learning and investment discussed here constitutes a relatively small part of the literature on social interactions. Models of social interactions have a wide range of applications. Some of the most active areas of research thus far have been: neighborhood influences on socioeconomic outcomes such as education attainment, income, labor force participation; spatial agglomeration; technology choices; interdependent preferences; and anti-social behaviour. See Brock and Durlauf (2001) for references.

learning by studying the experience of Indian farmers in adopting new high-yield varieties of crops. Both find evidence of social learning. A farmer's decision to adopt a new technology depends significantly on neighbors' behaviour. Foster and Rosenzweig find that learning from neighbors' experiences significantly increases a farmer's own rates of technology adoption and profitability. Munshi compares social learning in the adoption of seed varieties under different information conditions. He finds that social learning is more prevalent when agents face more homogeneous conditions.

Only one study that I am aware of examines firms' labour force adjustment decisions and social learning (Guiso and Schivardi, 2000). Using employment data from manufacturing firms in Italy, they find that similar neighbouring firms' actions significantly affect the labour force adjustment of the firm, but the actions of dissimilar or non-neighbouring firms have no influence. Their results imply that social learning is a significant factor in explaining the employment adjustment behaviour of firms exposed to information externalities. Furthermore, they find that extreme adjustments by like firms have a stronger influence than average adjustments, and that small firms appear to depend more on social learning than larger firms.

3. Theoretical Model Overview

CL94 model a firm's decision to suspend an irreversible investment that takes T periods to build. The firm pays a sunk entry cost κ , to begin the investment project and decides in each period whether to continue, suspend, reinitiate or cancel the project. Continuing involves a cost each period equal to one, but suspension is costless. Reactivation after suspension involves an additional cost of $\mu\kappa \geq 1$. The choices depend on the firm's perception of the true state of demand, which is either high or low. If demand is high at time

T , the firm sells one unit of output and receives revenue P_H , but if demand is low, the firm receives zero.

A firm's perception of demand is formed from three sources of information. First, it has its own prior knowledge about the state of demand, and, *ex ante*, the firm believes demand will be high so it undertakes the project. Second, each firm has private information in the form of a noisy signal. The private signals that a firm receives each period generate a vector of signals σ . The signal in a given period s takes the form $\sigma_s = \{\text{good, bad}\}$. The variable p reflects the information content or quality of the noisy signal. The probability that a firm receives a good signal when demand is actually high equals $p \in [0.5, 1]$. The probability of receiving a good signal when demand is actually low is $q = 1 - p$. The third source is the firm's observations of the history of all other firms' entry, continuation, suspension, reactivation and cancellation decisions.

CL show that equilibrium is defined as a strategy $\pi(c, z)$ and a quantity of entry E such that: π is optimal and uses all the information revealed when other firms also play π and there are E entrants; and, the *ex ante* expected profits are zero. The strategy $\pi(c, z)$ consists of the probability of continuing $c(I_s) \in [0, 1]$, and the probability of reinitiating if suspended, $z(I_s) \in [0, 1]$. The firm's information set in period s , I_s , consists of: the firm's private signals through period s , σ^s , and the history of other firms' behaviour through to period $s-1$. The exogenous variables are the demand function $P(Q)$; the length of the project T ; the cost of entry κ ; the re-activation cost $\mu\kappa$, and the information content of each signal p .

If there were complete information, firms would enter in period zero, and observe other firms' private signals in period one and immediately know the true demand state. They would then continue through to T or exit in period one and all uncertainty about demand

would be resolved. In CL94 that state of demand is not known until some firms reveal their private information by suspending. Therefore a private information phase covers periods $1 \leq s \leq t-1$, where t is the time of the first suspensions. In the private information phase, all firms are gathering their own private information and continuing their project. In period t , some firms suspend based on their private signals. In the basic model, these first suspensions have no social learning component; these agents act independently of others' behaviour. Caplin and Leahy prove there exists a set of symmetric Nash equilibria in which the proportion of firms that choose to suspend in period t is determined by the state of demand, and where these first suspensions reveal the true state of demand. After the first suspensions in period t , the uncertainty about the state of demand is resolved in this model.²⁶ If the proportion of firms that suspend is high, demand is low and if the proportion of suspensions is low, demand is high. Social learning occurs in periods $s > t$, when all firms have observed the period t suspensions and know the state of demand based on the behaviour of the first suspenders. They continue or restart (if they suspended in t) if demand is high, and they exit if demand is low.

The CL94 model's essence involves identifying the first suspension time t . Formally, CL94 find the equilibria by considering if some arbitrary period t is a first-suspension time by solving:

$$(1) \quad t = \min_s \{s \in [1, T] : c(I_s) < 1 \text{ for some } I_s \in \Omega_s(E)\}$$

where Ω_s is the set of all information sets corresponding to entry level E . The set of possible equilibrium first suspension times is identified by finding the upper and lower bound conditions for period t to be a first suspension time.

²⁶ This rather strong assumption of the model is weakened in extensions to the model, without changing the predictions of the model. This is discussed in more detail later.

The lower bound on the first suspension time T_L , is the earliest period in which suspensions may occur. The firm's beliefs about the probability of demand being high are assumed to be strictly increasing in the number of good signals that it receives. So firms with the fewest good signals are the most pessimistic about the state of demand, and they suspend first. So to find the earliest suspension time, CL consider when a firm with zero good signals chooses to suspend. The suspending firm must believe that the savings from suspending and not paying continuation costs if demand is low, exceed the cost of having to re-initiate if demand turns out to be high. This reasoning generates a condition for the lower bound T_L on the first suspension time:

$$(2) \quad T_L : \mu\kappa = \left(\frac{p}{q}\right)'$$

Equation (2) says that the first suspensions must occur late enough that the most pessimistic firms are willing to suspend and reveal their private information.

The expected value of continuing must be non-negative for all periods before t for all firms, even for one with no good signals. This condition and the free-entry condition that expected profits are zero allow CL94 to find an upper bound on the earliest suspension times T_U , in which $U(s,t) \geq 0$ for all periods $s \in [1, t-1]$, where $U(s,t)$ denotes the expected value in period s of continuing through period $t-1$ and following an optimal strategy for a firm with zero good signals. The upper bound, T_U may be expressed as:

$$(3) \quad \begin{aligned} T_U : \quad & U(s,t) \geq 0, \text{ where} \\ & U(s,t) = \frac{q^s}{p^s + q^s} [P_H - T - (t-1)] - (t-s) - \mu\kappa \Pr_s(\{h(\sigma_t) \leq h^*\} \cap \{H\}) \\ & \quad - \Pr_s(\{h(\sigma_t) > h^*\} \cap \{L\}) \end{aligned}$$

and where H and L denote the high and low demand states, respectively. The first term is the expected revenue less continuation costs that firms pay if demand is high. The second term is the continuation costs through period $t-1$. The third and fourth terms show the additional costs if the firm makes a mistake. Specifically, the third term shows the cost of having to reinitiate if it wrongly suspends in period t . The fourth term is the probability that the firm will pay the continuation costs in period t but demand is actually low. This upper bound on t says that since firms pay a continuation cost for every active period, firms that believe demand is low would rather not pay further costs.

The authors prove that an equilibrium first suspension period t exists if individual signals are sufficiently informative and the time horizon is sufficiently short.

4. Empirical Methodology

The main implication of the CL94 model tested here is the social learning hypothesis that the probability of a given firm suspending its project depends on the proportion of other firms suspending in the previous period. In the basic model, all uncertainty is resolved by the first suspensions. This is a strong assumption, however, CL also demonstrate that social learning will be present in a more realistic setting where uncertainty about demand is not resolved until the project is completed. In this scenario, when the first firms suspend, others observe their actions and update their beliefs, causing some to suspend and others to carry on. The continuing firms again gather private information until the next firm suspends at which time the market again aggregates the information and updates beliefs. Agents learn from the behaviour of others as well as their own private information, but the social learning occurs in several stages. This version of the model still predicts that other suspensions will influence a firm's decision to suspend, implying a positive relationship between the

proportion of other active projects suspended and the probability that a given firm will suspend.

Based on CL94, I model individual behaviour as a binary choice, to suspend or not suspend, using the probit model shown in equation (4). Note that the semiconductor data I use have plant-level, rather than firm-level observations, so the individual agent is a plant manager. The regression model is:

$$(4) \quad \Pr(Y_{it} = 1) = \Phi(c + \beta' X_i + \alpha' Y_{-it} + \phi' Z_r + \varepsilon_{it})$$

where $\Pr(Y_{it}=1)$ is the probability of suspension by plant i in region r at time t , where t is the end of the project. The suspension dummy variable $Y_{it} = 1$ if the plant chooses to suspend its project and $Y_{it} = 0$ if the plant completes its project. Φ is the cumulative standard normal probability distribution function. The first two terms on the right hand side are the constant term, followed by X_i , a vector of individual plant characteristics. X_i consists of the exogenous variables in the CL94 model: initiation cost, private signal quality, restart costs, and also a technology variable since the projects are not all identical. Initiation cost is measured as the expected construction cost component of the semiconductor project as a percentage of expected total costs. Private signal quality is operationalized by the total cost of the project, since firms that can undertake more expensive projects are assumed to be able gather better quality information. In all cases, cost expectations were formed at the beginning of the project. Differences in technology are captured by the size of the semiconductor wafers manufactured at the plant. Larger wafer sizes are usually associated with newer technology.

The social learning effect is captured through the variable Y_{-it} which is the percentage of other active plants in region r that have been suspended in period t , where t is the quarter when plant i 's project ended, either through completion or suspension. Active

projects are defined as those that have been initiated and were under construction in period t . In the CL94 model it is other suspensions in the *previous* period that would influence the current period's suspensions, however with quarterly data it seems more likely that a firm reacts to others' behaviour in the same period. However, in separate regressions, I also use one lag of Y_{-it} to check the validity of this assumption and I don't find any substantial differences.

Z_{it} is a vector of contextual regressors for region r in period t intended to capture the effect of common shocks and the influence of a common environment. In particular, Z_{it} includes the percentage change in regional semiconductor sales from the previous quarter or year, and a full set of year dummies interacted with region.

4.1 Hypotheses Tests

The key hypothesis to test is that if social learning is present the coefficient on Y_{-it} , α , is positive, and if social learning does not affect the individual plant's suspension decision then α equals zero.

The CL94 model also generates testable hypotheses in the form of sign predictions for the X_i variables. CL work out the comparative static effects of changes in the exogenous variables on equations (2) and (3), the lower and upper limit of first suspension times. To facilitate empirical tests using a probit model, I interpret CL's comparative statics in terms of whether a change in the exogenous variable increases or decreases the probability that an individual project is suspended.

CL show that increases in the initiation cost κ reduce the set of equilibria involving suspensions and thus reduce the probability that a given firm suspends its project. So I expect the β coefficients on the initiation cost to have negative coefficients. An increase in

initiation costs increases the price of the good in the high-demand state, such that it takes more bad news to convince the firm to suspend its project, which pushes back the first suspensions, and reduces the number of suspensions the one is likely to observe.

Increases in the quality of the firm's private signals (p) are summarized by CL as follows: "the more convincing is each individual signal, the fewer signals a firm needs to justify suspension." (CL94, p.559) Better quality private information decreases both the lower and upper bounds on equilibrium suspension times. This implies that suspensions occur sooner in the project, reducing the delay due to social learning and making it more likely that I observe suspensions in the low-demand state. Higher quality private signals should also result in less reliance on social learning. Therefore other firms' suspensions are expected to have less influence on firms with good private information.²⁷

4.2 Identification

Manski (1993, 2000) points out that an important problem of identifying social effects parameters arises when estimating social learning models. The problem occurs because of the likelihood that reference group determinants and individual determinants of individual behaviour are likely to be correlated. The actions of individual agents in a reference group are related to the group's mean, but not always because of social learning. Manski offers three reasons for the correlation of individual and group behaviour:

"(a) *endogenous* effects, wherein the propensity of an individual to behave in some way varies with the behaviour of the group; (b) *exogenous* (contextual) effects, wherein the propensity of an individual to behave in some way varies with the exogenous characteristics of the group, and (c) *correlated* effects, wherein individuals in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments" Manski (1993, p.532).

²⁷ The model also predicts that an increase in the cost of re-entry, μ , decreases the set of equilibrium suspension times and reduces the probability of observing a suspension for a given firm. The dataset does not include a variable on re-entry costs, so this prediction is not tested.

Brock and Durlauf (2001) analyze the identification problem in social interaction models. They show that identification of the endogenous social effects can be achieved in a binary choice model if the individual and contextual regressors are not linearly dependent, and if the average group choice is a nonlinear function of the contextual effects. (Brock and Durlauf, p.3322) I use these criteria to verify if the model in equation (4) is identified.

Since semiconductor plant owners or customers or both are often located in different continents, it is not obvious what the appropriate reference group should be. Initially, I treat the whole industry as operating in one group. I also consider social effects arising between firms located in the same region, so for some regressions, plants are grouped with other plants in the same region: Europe, North America, Japan, and Asia-Pacific. The relatively small number of observations in the dataset does not allow smaller groupings. The data are explained in more detail below.

To satisfy the first part of the identification conditions described by Brock and Durlauf (2001), individual plant characteristics, X_i , cannot be linearly dependent on the contextual regressors, Z_{it} . Recall that X_i includes: initiation costs, measured as expected construction costs as a percentage of expected total costs; expected total cost as a proxy for signal quality; and wafer size. All of the X_i variables are determined at the beginning of the project. The Z_{it} variables consist of: year-region dummies and aggregate semiconductor sales growth, i.e. quarterly or annual percentage change in regional sales measured at the end of the project. Given the differences in timing, it is unlikely that there is a linear relationship between the X_i and Z_{it} variables.

However, it is possible that a linear relationship exists between the average group behaviour, Y_{it} , and the contextual effects, Z_{it} , since both are measured at time t and are expected to be correlated. Intuitively, changes in the overall demand conditions could cause

plants to suspend at the same time, not because of social learning, but because they face the same environment, leading to non-identification due to correlated effects described by Manski. However, if the other suspensions variable, Y_{-it} is a *nonlinear* function of the contextual effects, Z_{it} , the model should be identified based on Brock and Durlauf's criteria. I use a RESET (omitted variable) test for nonlinearity between these variables as recommended in Davidson and MacKinnon (1993, p.195).

When the whole dataset is treated as one group, the RESET test involves regressing the percentage of other projects suspending (Y_{-it}) on year dummies and aggregate sales growth (either annual or quarterly). The p -values for these tests, first using annual sales growth and then using quarterly sales growth, were 0.000 and 0.002 respectively. With regions as reference groups, the percentage of other suspensions in the region is regressed on the year-region dummies and regional sales growth. The p -values for the RESET tests with regional variables were 0.001 and 0.003. Both sets of test results reject a linear relationship between the average group behaviour and the contextual regressors. These results indicate the model in equation (4) should be sufficient to identify the social learning effects via the coefficient estimate for Y_{-it} .

5. Data Description

I use semiconductor plant-level data from a commercial database called World Fab Watch (WFW) produced by Strategic Marketing Associates, a semiconductor industry research firm based in Santa Cruz, California. WFW contains data on semiconductor firms' investments in semiconductor fabrication plants, called "fabs". The investment projects consist of either the construction of new plants or major upgrades to existing facilities. The data are collected on a monthly basis through site visits, telephone interviews and email

enquiries. Strategic Marketing Associates estimate that the database covers more than 95% of the commercial semiconductor fabrication plants in the world. The database includes detailed data on each plant, including the company, location, country of ownership, beginning and ending dates for construction or upgrade of the plant, production technology, products to be produced, and total expected costs of the project, broken down into construction costs and equipping costs.

I select a sample from the WFW database by first removing plants owned by governments, universities or other not-for-profit organizations. Second, I remove plants where the firm has only announced that it intends to build or upgrade a fabrication plant but construction has not yet begun. I omit these projects since there may be no initiation cost actually incurred, so the suspension would not release as much information as the suspension of a project that had been underway.

In some cases where dates or costs of the project were missing I could obtain the missing data from the industry and business news in the Lexis Nexis news database, or from Internet versions of semiconductor industry newspapers including: *Semiconductor News*, *Electronic Buyers News*, and *Silicon Strategies*. In two cases, Internet versions of local newspapers in New England and Colorado provide information about a plant. In total, 23 projects have some data obtained from news sources.

The period studied consists of 30 quarters from January 1, 1995 and to June 30, 2002. This period was selected because prior to that, original production dates were not identified in the WFW database. Although the dates consist of at least the month and year the activity occurred, I group the data into quarters since some of the date variables (begin work date, production date, delay announcement date) come from news articles only, rather than WFW itself. The news articles' dates may be less precise than the dates contained in the

original WFW database, so I only attempt to identify the quarter and year in which the activity on the project occurred. These selection criteria leave 258 plants for which the construction or upgrade investment project was begun during the 30-quarter period studied.

I identify suspended or cancelled projects where there was a delay announcement date and/or comments noting a delay in the project in the WFW database. I also identify some suspensions by comparing the original production date with the actual production date. If there are differences in these dates of six months or more, I search news sources to see if a suspension has been reported for that plant. Through correspondence with the authors of the WFW database, I also identify three cancelled projects and obtain clarifications on some of the other suspension details. Of the 258 semiconductor plant investment projects in the sample, 36 are suspensions and three are cancellations. Throughout the paper, the 39 suspensions and cancellations are grouped together and referred to as suspensions. Figure 1 summarizes the semiconductor fab project initiations and suspensions by quarter for the sample plants.

The sample data shown in Figure 1 show a reasonably lumpy pattern of initiations and suspensions of semiconductor plant investments. Suspensions are grouped into two periods, 1996:Q2 to 1998:Q4 and 2000:Q4 to 2002:Q1. In these periods, initiations fall off as suspensions rise, leading to large spikes in the ratio of suspensions to initiations. Aggregate industry semiconductor sales are shown in Figure 2 over the study period. The aggregate data are based on monthly data on worldwide billings of semiconductor shipments published by the U.S. Semiconductor Industry Association.²⁸ Over the period 1995Q1 to 2002Q2 there were fairly large fluctuations in shipments, especially in North America. These

²⁸ All sample data on costs and aggregate sales were originally in nominal U.S. dollars. Dollar values are converted to the 1996 U.S. dollars using the U.S. GDP implicit price deflator Published in Table 7.1 on the Internet website for the Bureau of Economic Analysis, Oct.31, 2003.

fluctuations roughly correspond to the pattern of project initiations in the sample of plants shown in Figure 1. Both figures indicate that the industry features a “boom and bust” pattern of sales and investment. As such, a social learning model may be appropriate to explain the investment behaviour in this industry.

Table 1 provides summary statistics for the variables used as regressors in the estimation model described above. Initiation cost is measured by the construction costs as a percent of total costs. Initiation costs average 17.5 percent of the total costs of the respective project. The total costs average \$593 million (in 1996 dollars) across the sample of investment projects. To capture social learning effects, I calculate the percentage of other plants’ investment projects that are suspended at the end of the plant’s own project (either through completion or suspension). For the average plant in the sample, 3.1% of other projects were suspended in the quarter when the plant’s own project ended. Aggregate industry sales growth is calculated as of the end of the project. Aggregate sales fell by 4.4 percent between the previous year and the end of the average project. Aggregate sales growth from the previous quarter to the end of the project averaged -0.4 percent.

A comparison between suspended and continued projects (either completed or continuing at the end of the sample period) is presented in Table 2. Most of the investment activity over the whole period occurs in North America and Asia excluding Japan (referred to as Asia Pacific here). Of the 39 suspended projects, 12 are located in North America and 16 in Asia Pacific. Japan and Europe had five and six suspended projects respectively. Suspended projects made up 15% of all projects, and 30% of the total expected costs. Japan had the lowest percentage of projects suspended while the rest of Asia-Pacific had the highest percentage. Suspended projects are, on average, nearly twice as expensive as

continued projects. The ratio of total costs of suspended to continued projects ranged from a low of 0.15 in Japan to 0.58 for North America.

6. Results

6.1 Estimates of Social Learning in Semiconductor Plant Suspension Decisions

Table 3 presents the results of estimating the basic model in equation (4) using probit regressions. The specifications in columns 1 and 2 assume all plants belong to the same reference group, and therefore may be influenced by suspensions anywhere else in the world. In columns 3 and 4 plants are divided into four reference groups based on their geographic region. These models assume that only other firms in the plant's own region could generate social learning. The final two columns include an additional regressor, a dummy variable for large plants interacted with the social learning term. This tests whether large plants rely less on social learning, assuming they have better quality information, as hypothesized in the CL94 model. Large plants are those with total costs greater than the median plant in the sample.

The variables measuring the plant's own investment project characteristics (X_i) all have the expected signs and are significant at the 1% level in all but two cases. As predicted, projects with higher initiation costs as a share of total costs have a lower probability of suspension, consistent with the comparative statics prediction. Higher cost projects are more likely to be suspended. To the extent that total cost is a proxy for the quality of private information that the plant has, this finding suggests that better-informed plants are more likely to suspend their projects. This finding is also consistent with the predictions of the CL94 model. A plant with good information is less likely to delay its decision to suspend (either to observe others or to gather more private information), and therefore one is more

likely to observe a suspension by these plants. Wafer size controls for the type of technology the plant will use. Larger wafer size technology is usually more complex, and my findings indicate that it is associated with a greater probability of suspension. I explore this finding in more depth in the regressions shown in Table 5, discussed below.

The key hypotheses involve the coefficient on other plants' behaviour (Y_{-it}), measured by the percentage of other active projects suspended at the end of the plant's own project. The main finding from Table 3 is that *none* of the social learning variables, *OTHER SUSPENSIONS*, *OTHER REGIONAL SUSPENSIONS* and *LARGEXOTHER SUSP.*, have the expected positive sign, and six of eight coefficients are not significant at the 5% level. To verify the timing of the social learning variable I have also included one quarter lags of *OTHER SUSPENSIONS*_{*t-1*}, individually and in combination with the same quarter observation in additional regressions, not presented in Table 3. The results are qualitatively the same regardless of whether the current quarter, one lag or both observations on the other suspension variables are included. The findings from the basic model regressions suggest that social learning is not a significant factor in the decision to suspend one's investment project. I also test the robustness of this result by weighting the other suspensions by project cost, and by duration, as shown in Table 4. The results in Table 4 reinforce the findings of the basic model here. Table 4 is discussed in more detail below.

The regional social learning effects in Table 3 are negative and significant, which is somewhat puzzling. This means other suspensions in the same region reduce the probability that a given firm suspends its project. Caplin and Leahy suggest that if firms behave strategically, a "war of attrition" scenario may occur — firms continue even when their signals are bad, hoping others will suspend, making the market more profitable for the remaining firms. This possibility could be explored in future research.

A secondary hypothesis from the CL94 model is that firms with better quality private information rely less on social learning than other firms. Columns 5 and 6 test this idea by interacting the social learning variable with a dummy variable to identify the plant's own project as large (greater than the median total cost) or not. If the large plants rely less on social learning, the coefficient on *LARGE X OTHER SUSP.* would be significantly smaller than the coefficient on *OTHER SUSPENSIONS*. However, a statistical test that the two coefficients are equal cannot be rejected, implying that there is no significant difference between large and small plants with respect to social learning.²⁹ In particular, other suspensions do not significantly influence the plant's own suspension behaviour.

The models in Table 3 assume that plants put equal weight on all other suspensions. Of course, it is also possible that the behaviour of some plants is more influential than others. So weighting the other suspensions in some way may reveal social learning effects not present in the basic regression models. I weight other suspensions in two different ways: by total cost and by duration.

Table 4 presents the results of the regressions when the other suspensions are weighted by cost or duration. In all four regressions, the X_i variables are all significant and have the same signs as before. In columns 1 and 2, *OTHER SUSPENSIONS* is simply the dollar value of other suspended projects based on total costs. In column 2, only other suspensions with total costs greater than the median value are included. This is intended to capture possible non-linear effects such that only the largest other suspensions influence plant i 's decision. Column 3 also uses other suspensions weighted by total cost, but the *OTHER SUSPENSIONS* variable is calculated as the dollar value of other suspensions as a

²⁹ The p-values for the test that the estimated coefficients on *OTHER SUSPENSIONS* and *LARGE X OTHER SUSP.* are equal were 0.3619 for column 5 and 0.3805 for column 6.

percentage of the value of all projects active at that time. In all three columns, the social learning variables have a negative sign and are not significant even at the 10% level. Column 4 uses duration of the suspended projects to weight their possible influence. Caplin and Leahy argue that “the probability other firms have received good signals will grow, the longer they remain in the market” (CL94, p.562). Projects that have been under construction for many periods have probably received several good signals and have had more time to incur costs. Therefore the suspension of a relatively long-lived project should release more information to the market than the suspension of a shorter-duration project. However, I find that weighting the other suspensions by their duration still does not change the finding that social learning does not appear to be a significant influence in explaining the suspension behaviour of semiconductor plants.

6.2 Estimates of Social Learning in the Adoption of 12 Inch Wafer Technology

Social learning models attempt to explain an agent’s decision making in the face of uncertainty. A potentially important source of uncertainty in this industry is the technical or economic feasibility of new technologies. The sample period includes the earliest adoption of a new generation of semiconductor production technology, 12 inch wafers, in mass production fabrication facilities. The previous standard had been 8 inch wafers and the switch to 12 inch wafers is a significant technological change requiring large investments in facilities. The average expected total cost of a 12 inch wafer plant in the sample is \$1.3 billion in 1996 U.S. dollars. The first 12 inch wafer R&D plant in the sample was completed in 1997, and the first production plant was completed in 1999. Of the 28 plants with 12 inch wafer technology, nearly half, 12, were suspended.

The experience of the semiconductor industry in adopting a significant new technology provides another opportunity to test the social learning hypotheses. Firms may rely on social learning not just to form beliefs about demand conditions, but also about the optimal time to adopt a new technology. Note this is not just a technological or R&D spillover. It is not necessary for any technical knowledge about how to manufacture semiconductors using 12 inch wafers to be transferred between firms. Instead, social learning theories imply there is an information spillover whereby the firm learns about the potential profitability of investing in the new technology just by observing whether or not others continue their investment project.

Table 5 presents the results of regressions testing for social learning by firms adopting this new technology. To do so, a dummy variable identifying 12 inch wafers was added to the regression and also interacted with the other suspensions variable. The first two columns assume a single, world region as the reference group and the key variable is *OTHER SUSP. X 12 INCH WAFERS DUMMY*. Columns three and four include regions as reference groups and the key variable is *OTHER REGIONAL SUSP. X 12 INCH WAFERS DUMMY*. The 12 inch wafers dummy variable on its own is not significantly different from zero, indicating that the intercept term does not differ between 12 inch fabs and other plants, so I focus on the two interactions terms.

The main result here is that the coefficient on the interaction variables for other suspensions x 12 inch dummy variable is positive and significant at the 5% level in all four regressions. This means that plants attempting to adopt the new wafer technology were significantly more likely to suspend their new 12 inch wafer plant if any other projects had been suspended. Interestingly, the other plants, those using the conventional, smaller wafers technology were significantly *less* likely to suspend their plant if there was another

suspension, as can be seen by the significant but negative coefficients on the *OTHER SUSPENSIONS* and *OTHER REGIONAL SUSP.* variables.

First, let's consider the 12 inch wafer plants. Suspensions by other plants elsewhere in the world, or in the plant's own region significantly increase the probability that these 12 inch wafer plants would be suspended. Note that the other suspensions are not only plants using 12 inch wafers they may be have any wafer size technology. When I treat the world as one region, the *OTHER SUSP. X 12 INCH WAFERS DUMMY* has a coefficient of 0.29 in both columns 1 and 2. Converting this probit index to a standard change in probability using the mean values of the regression variables, the 0.29 coefficient implies that a 1% increase in the number of other plant suspensions (anywhere in the world) increases the probability of suspension for a given plant by 3.6%. If I only consider other suspensions in the same region, the probit regression coefficients are 0.16 to 0.17, shown in columns 3 and 4. Transforming these coefficients into probabilities evaluated at the mean, I find that a 1% increase in the number of other suspensions in the region increases the probability of suspension of an average plant by 1.6% to 1.7%. So the economic significance of these finding is not large, but they do suggest that social learning may be more important for agents facing greater uncertainty. Another possible explanation is that when deciding to adopt an unknown, new technology the firm's private information is not as good as when the firm is deciding to suspend a project with known technology.

Another interesting result from the technology choice regressions is that the firms using conventional technology behave differently from the firms adopting the new technology. Specifically, I see from the negative and significant coefficients on the *OTHER SUSPENSIONS* and *OTHER REGIONAL SUSP.* variables that the firms using the old technology are less likely to suspend their project when others suspend. Converting the

coefficients on *OTHER SUSPENSIONS* to probabilities evaluated at the mean, I find that a 1% increase in the number of suspensions by other firms reduces the probability of suspension for the average firm by 1.4%. For the *OTHER REGIONAL SUSP.* variable, the coefficients in columns 3 and 4 imply that a 1% increase in other suspensions in the same region reduces the probability that the average firm suspends their project by 1.1% to 1.2%.

One explanation for the negative relationship between other suspensions and the plant's own suspension when the plant will use the older technology is that these plants decision is based more on a war of attrition game than learning from others. Since they know what to expect with respect to output and costs with the existing technology, their suspension decision may be more driven by continuing when rivals suspend because it will allow them to capture a larger share of the market. By contrast, when a firm is adopting a new technology they face more uncertainty concerning costs, output, productivity and ultimately profits that will be generated by the new plant. Therefore their decision to suspend is more sensitive to worries that demand is weakening, so if a rival firm stops building its plant, the new technology adopter is more likely to suspend as well.

6.3 Robustness to Alternative Sales Shock Specification

The preceding analysis assumes aggregate demand shocks can be approximated by sales growth variables measured using the percentage change in aggregate worldwide (or regional) shipments value from the previous year or quarter. An alternative method is to forecast aggregate sales and use the residuals from the forecast regression to represent aggregate sales shocks. The forecast regression uses OLS to estimate the AR(4) model

shown in equation (5). Since the data are quarterly, four lags of aggregate sales enter the forecast equation.³⁰

$$(5) \quad SALES_t = SALES_{t-1} + SALES_{t-2} + SALES_{t-3} + SALES_{t-4} + v$$

The regression residuals from equation (5) are used as a Z_t regressor, called *AGGREGATE SALES SHOCK*, in the probit regressions in place of the aggregate sales growth variables. Table 6 presents the results of the probit regressions of the basic model and the 12-inch wafer technology choice model using the aggregate sales shock variable. The basic model is shown in column one and the technology choice model is shown in the second column. The results using the sales shock variable are not qualitatively different from those reported above. The basic model does not have a significant social learning effect, while the firms adopting the 12 inch wafer technology are positively and significantly affected by the suspensions of other projects.

7. Conclusions

Overall, the research here indicates that the decision to continue or suspend an investment project is not significantly influenced by the suspensions by other similar plants in this industry. However, when investing in a major new technology, social learning does seem to occur in the semiconductor fabrication industry. Plants adopting a new generation of wafer technology are significantly more likely to suspend their project if other suspensions occur in the same period. Plants adopting conventional technologies are not significantly influenced by the behaviour of others when deciding to suspend their project, in fact other suspensions reduce their probability of suspending. These findings may indicate that social

³⁰ I also use a forecast model with eight lags of aggregate sales data which did not result in any substantial changes in the findings.

learning is associated with conditions where uncertainty is unusually high, like the adoption of a new technology, or when the agent's own private information is not very good. Further work is required to establish more generally the conditions under which agents rely on private information versus social learning.

Earlier work on technology adoption found significant social learning effects in datasets that feature relatively simple, non-capital intensive technologies in agriculture. This paper approaches the question of social learning from the opposite direction by considering when an investment project is suspended, which allows us to compare suspenders and a control group of non-suspenders. Using data from a highly capital-intensive industry with complex technologies, I also find evidence that social learning influences technology adoption decisions.

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Figure 1: Semiconductor Fabrication Plants Investment Projects Initiated and Suspended Per Quarter, Worldwide

Source: Author's calculations based on World Fab Watch Database and semiconductor industry news sources.

Figure 2: Semiconductor Shipments per Quarter, Worldwide, 1996 U.S. Dollars, billions

Source: Global Billings Report History, Semiconductor Industry Association

Table 1: Semiconductor Plant Investment Projects Summary Statistics
Total Costs in 1996 U.S. Dollars, millions

	Mean	Median	Std. Dev.	Obs.
Initiation Cost as % of Total Cost	17.5	20.0	10.6	255
Total Cost	593.7	413.9	596.7	258
Wafer Size (inches)	7.5	8.0	2.1	257
Other Suspensions as % of Other Active Projects	3.1	1.5	3.2	258
Aggregate Sales Growth (% yr/yr)	-4.4	-2.7	21.7	258
Aggregate Sales Growth (% qtr/qtr)	-0.4	0.1	9.4	258

Table 2: Suspended and Continued Projects By Region
Total Costs in 1996 U.S. Dollars, millions

	Asia-Pacific	Europe	Japan	North America	World
Suspended Projects:					
Number	16	6	5	12	39
Avg. Total Cost (TC)	1,364	1,421	641	1,098	1,198
Sum of Total Costs (Σ TC)	21,829	8,529	3,205	13,178	46,741
Continued Projects:					
Number	61	46	49	63	219
Avg. Total Cost (TC)	746	340	464	358	486
Sum of Total Costs (Σ TC)	45,461	15,654	22,747	22,565	106,428
Σ TC (Suspended)	0.48	0.54	0.14	0.58	0.44
/ Σ TC (Continued)					

Table 3: Probit Regressions for Basic Models
Dependent Variable is Suspension = (1,0)

	(1)	(2)	(3)	(4)	(5)	(6)
INITIATION COST (%)	-0.0577 (-3.70)	-0.0587 (-3.59)	-0.0615 (-3.65)	-0.0641 (-3.50)	-0.0692 (-3.74)	-0.0703 (0.00)
TOTAL COST (\$)	0.0012 (4.09)	0.0012 (4.01)	0.0008 (2.69)	0.0008 (2.59)	0.0019 (4.63)	0.0019 (0.00)
WAFER SIZE	0.1981 (2.39)	0.1900 (2.26)	0.3428 (3.32)	0.3357 (3.37)	0.2532 (1.08)	0.2615 (0.28)
OTHER SUSPENSIONS (%)	-0.0268 (-0.54)	-0.0376 (-0.79)			-0.0113 (-0.14)	-0.0165 (0.84)
OTHER REGIONAL SUSP. (%)			-0.0732 (-2.26)	-0.0876 (-2.86)		
LARGE X OTHER SUSP. (%)					-0.1453 (-1.76)	-0.1443 (0.0750)
AGG. SALES GROWTH (%) (annual)	0.0006 (0.05)				-0.0109 (-0.60)	
AGG. SALES GROWTH (%) (quarterly)		-0.0175 (-0.86)				-0.0004 (0.98)
REGIONAL SALES GROWTH (%) (annual)			0.0043 (0.28)			
REGIONAL SALES GROWTH (%) (quarterly)				-0.0276 (-1.16)		
N	227	227	180	180	200	200
Wald chi2	37.96	41.28	.	.	59.95	59.72
Pr > chi2	0.0000	0.0000	.	.	0.0000	0.0000
Pseudo R2	0.3638	0.3673	0.4216	0.4308	0.3946	0.3914

Coefficients are shown above with t-statistics below in parentheses. All regressions include a constant and year dummies interacted with region dummies. Year or quarter refers to the period when the project was completed or suspended. Dollar values are in 1996 U.S. dollars; converted from nominal dollars using U.S. GDP deflator. All regressions use robust standard errors. Columns (5) and (6) exclude plants with twelve inch wafer technology. In (5) and (6) the large dummy equals one if the plant's own project has expected total costs greater than the median project in the whole sample.

Table 4: Probit Regressions with Weighted Other Suspensions
Dependent Variable is Suspension = (1,0)

	(1)	(2)	(3)	(4)
INITIATION COST (%)	-0.0592 (-3.63)	-0.0594 (-3.65)	-0.0590 (-3.61)	-0.0595 (-3.68)
TOTAL COST	0.0012 (3.93)	0.0012 (3.93)	0.0012 (3.95)	0.0012 (4.07)
WAFER SIZE	0.1906 (2.24)	0.1905 (2.24)	0.1920 (2.26)	0.1918 (2.27)
OTHER SUSPENSIONS (Wgt \$)	-0.0001 (-1.01)			
OTHER SUSPENSIONS (%) (\$ Value as % of Other Active)			-0.0193 (-0.86)	
OTHER LARGE SUSP. (\$)		-0.0001 (-1.12)		
DURATION OTHER SUSP. (quarters)				-0.0267 (-1.40)
AGG. SALES GROWTH (%) (quarterly)	-0.0240 (-1.08)	-0.0255 (-1.13)	-0.0193 (-0.90)	-0.0235 (-1.10)
N	227	227	227	227
Wald chi2	39.78	39.92	39.91	44.15
Pr > chi2	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.3696	0.3707	0.3684	0.3731

Coefficients are shown above with z-statistics below in parentheses. All regressions include a constant and year dummies. Year or quarter refers to the period when the project was completed or suspended. Dollar values are in 1996 U.S. dollars; converted from nominal dollars using U.S. GDP deflator. All regressions use robust standard errors. The other plants' suspensions are weighted by the expected costs of the project. The model in (2) includes only other suspended projects that are large, defined as having expected total costs greater than the median project in the whole sample.

Table 5: Probit Regressions with Technology Choice Dummy
Dependent Variable is Suspension = (1,0)

	(1)	(2)	(3)	(4)
INITIATION COST (%)	-0.0572 (-3.72)	-0.0588 (-3.61)	-0.0551 (-3.21)	-0.0581 (-3.07)
TOTAL COST	0.0014 (4.72)	0.0013 (4.64)	0.0013 (4.91)	0.0013 (4.70)
12 INCH WAFERS DUMMY	-0.3888 (-0.64)	-0.4087 (-0.72)	0.1057 (0.15)	0.1653 (0.25)
OTHER SUSPENSIONS (%)	-0.1000 (-1.74)	-0.1121 (-2.01)		
OTHER SUSP. X 12 INCH WAFERS DUMMY	0.2913 (2.79)	0.2921 (2.95)		
OTHER REGIONAL SUSP. (%)			-0.1000 (-2.98)	-0.1155 (-3.34)
OTHER REGIONAL SUSP. X 12 INCH DUMMY			0.1636 (2.06)	0.1574 (2.08)
AGG. SALES GROWTH (%) (annual)	-0.0017 (-0.13)			
AGG. SALES GROWTH (%) (quarterly)		-0.0187 (-0.96)		
REGIONAL SALES GROWTH (%) (annual)			0.0058 (0.41)	
REGIONAL SALES GROWTH (%) (quarterly)				-0.0286 (-1.18)
N	227	227	180	180
Wald chi2	37.36	38.28	.	.
Pr > chi2	0.0001	0.0001	.	.
Pseudo R2	0.3928	0.3967	0.4234	0.4326

Coefficients are shown above with z-statistics below in parentheses. All regressions include a constant and year dummies. Year or quarter refers to the period when the project was completed or suspended. Dollar values are in 1996 U.S. dollars; converted from nominal dollars using U.S. GDP deflator. All regressions use robust standard errors.

Table 6: Probit Regressions Using Alternative Sales Shock Variable
Basic Model and Technology Choice Model
Dependent Variable is Suspension = (1,0)

	(1)	(2)
INITIATION COST (%)	-0.0601 (-3.59)	-0.0602 (-3.62)
TOTAL COST	0.0011 (3.96)	0.0013 (4.66)
WAFER SIZE	0.1889 (2.33)	
12 INCH WAFERS DUMMY		-0.3738 (0.65)
OTHER SUSPENSIONS (%)	-0.0623 (-1.29)	-0.1234 (-2.41)
OTHER SUSP. X 12 INCH WAFERS DUMMY		0.2828 (2.82)
AGGREGATE SALES SHOCK (residual from AR(4) forecast)	-0.1202 (-1.43)	-0.0982 (1.20)
N	227	227
Wald chi2	42.54	42.44
Pr > chi2	0.0000	0.0000
Pseudo R2	0.3736	0.3994

Coefficients are shown above with z-statistics below in parentheses. All regressions include a constant and year dummies. Year or quarter refers to the period when the project was completed or suspended. Dollar values are in 1996 U.S. dollars; converted from nominal dollars using U.S. GDP deflator. All regressions use robust standard errors. Aggregate sales shock is the residual from an auxiliary regression using the aggregate data on worldwide semiconductor shipments data described in the text. A simple OLS regression equation was used to forecast aggregate sales.