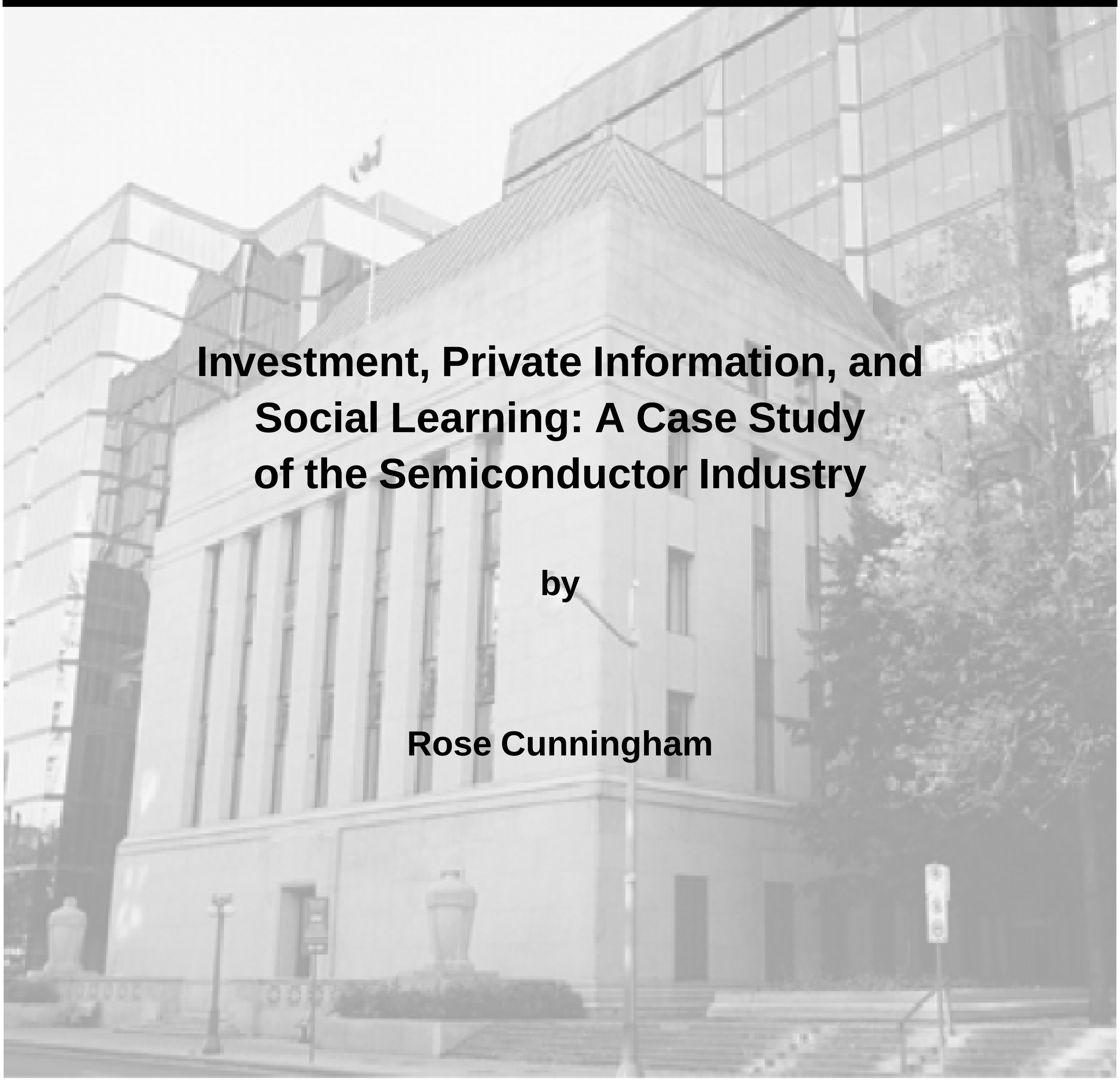
Bank of Canada Banque du Canada

Working Paper 2004-32 / Document de travail 2004-32



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

by

Rose Cunningham

ISSN 1192-5434

Printed in Canada on recycled paper

Bank of Canada Working Paper 2004-32

September 2004

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

by

Rose Cunningham

International Department
Bank of Canada
Ottawa, Ontario, Canada K1A 0G9
rcunningham@bankofcanada.ca

Contents

Acknowledgements

I thank Huntley Schaller, Stephen Ferris, and Rose Anne Devlin for their advice on this paper. Helpful comments were also provided by Larry Schembri, Eric Santor, Robert Lafrance, Robert Fay, Jean-François Perrault, and seminar participants at the Bank of Canada.

Abstract

Social learning models of investment provide an interesting explanation for sudden changes in investment behaviour. Caplin and Leahy (1994) develop a model of social learning in which agents learn about the true state of demand from the investment suspension decisions of other agents. The author tests the main predictions of Caplin and Leahy's model using a unique database of investment projects undertaken by semiconductor plants. She finds that firms that are installing a significant new technology appear to be influenced by social learning, because they are more likely to suspend their investment project when other suspensions occur. A 1 per cent increase in the number of other suspensions increases by 3.6 per cent the probability that an average new technology plant will suspend their investment project. Suspensions by other agents also significantly affect plants that use conventional technology, but that effect is negative. The conventional technology plants are less likely to suspend their investment project when other firms suspend, which suggests that their payoffs are strategic substitutes, as in a "war-of-attrition" game.

JEL classification: E32, L63, C35
Bank classification: Business fluctuations and cycles

Résumé

Les modèles basés sur l'apprentissage social dans les décisions d'investissement expliquent de manière intéressante les changements brusques observés dans le comportement des investisseurs. Caplin et Leahy (1994) ont mis au point un modèle de ce genre où les agents déduisent le véritable état de la demande des décisions que prennent d'autres agents de suspendre leurs projets d'investissement. L'auteure teste les principales prédictions du modèle de Caplin et Leahy à l'aide d'une base de données unique regroupant des informations sur les projets d'investissement de fabricants de semiconducteurs. Il ressort de l'étude que les entreprises qui ont commencé à installer une technologie radicalement nouvelle semblent influencées par le comportement qu'elles observent chez leurs concurrents. Elles paraissent en effet plus enclines à surseoir à leur projet d'investissement quand d'autres entreprises prennent une décision en ce sens. Une hausse de 1 % du nombre de suspensions entraîne une augmentation de 3,6 % de la probabilité de voir un fabricant ayant entrepris de se doter d'une nouvelle technologie renoncer à son projet. Les suspensions de la part d'autres agents ont aussi un effet important, mais cette fois opposé, sur les fabricants qui optent pour une technologie courante. Ces fabricants sont moins portés à emboîter le pas à leurs concurrents, ce qui semble indiquer qu'ils tirent leurs bénéfices de produits qui constituent des substituts stratégiques, comme s'ils étaient engagés dans une « guerre d'usure ».

Classification JEL : E32, L63, C35
Classification de la Banque : Cycles et fluctuations économiques

1. Introduction

Aggregate investment has historically been one of the most volatile components of GDP over the business cycle. Despite its importance, the reasons for volatility in investment spending, and thus one of the main sources of business cycle fluctuations, 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: finance constraints, irreversibility of investment, measurement error in *q*, aggregation over heterogeneous investment goods, and the lumpiness of investment spending at the firm level.[1]

Social learning theories of investment provide an interesting explanation for investment volatility. Social learning is the process of gaining information from observing the behaviour of others.[2] Conventional models of learning and investment produce fairly gradual changes in aggregate behaviour, but social learning models can produce abrupt changes, consistent with the observed patterns of aggregate investment. Since the actions of other agents contain information about their private beliefs, an agent may base their actions at least partially on what they observe others doing.

Social learning theories explain phenomena such as herd behaviour and sudden changes in widely held beliefs. Therefore, social learning provides a means for small shocks to be amplified, because actions taken by a few agents can change the beliefs of many others and cause them to act simultaneously. This clustering of many firms' actions can generate a boom or a crash in aggregate investment spending.

In these models, there is uncertainty about an important state variable, such as demand, about which agents have private beliefs. Agents use Bayes' rule to update their private

1. Caballero (1999) provides a survey and references.
2. The literature also refers to "observational learning" or "information externalities."

beliefs after an action is taken by another market participant. Since actions at least partially reveal an agent's private information, many agents delay their own action to learn more about demand conditions by observing others. Significant actions taken by a few agents can thereby dramatically change the beliefs held by many others and lead to a sudden change in their behaviour. For example, if demand is widely believed to be strong, but then a few firms stop their investment projects, others may become pessimistic about demand and also reduce their investment spending, generating a large decrease in aggregate investment spending.

This paper tests the implications of a model of social learning and capital investment developed by Caplin and Leahy (1994) (CL94). Empirical tests of social learning models of investment are rare; this paper provides some of the first empirical tests using capital investment data. I test the main social learning hypothesis from CL94 that, other things being equal, more suspensions by other firms increase the probability that a given firm will suspend its investment. I use a unique database of 258 semiconductor fabrication plants that had investment projects underway over the period 1995 to 2002.

By studying a single industry, the heterogeneity of capital investment projects is greatly reduced, which makes it much simpler to control for differences in production technology across plants. The semiconductor industry allows a useful case study for several reasons. It is an economically important industry, having had worldwide shipments of $25 billion to $50 billion per year in 1996 U.S. dollars. From a macroeconomic perspective, it is a highly cyclical industry, as shown by the investment and shipments data in Figures 1 and 2. Semiconductors are also important inputs for industries such as computers and telecommunications—industries that played a large role in the expansion and subsequent collapse in aggregate investment spending in the United States from 1995 to 2001. Therefore, semiconductor plants represent a large, cyclical industry that is closely connected to industries that led the aggregate fluctuations during the most recent business cycle.

I find that social learning is a significant factor in the decision-making process of semiconductor plants, but there are striking differences in the social learning behaviour of those investing in conventional technologies compared with those adopting a significant new technology.[3] Semiconductor plants that use conventional technology appear to react in opposition to the actions of others, such that a given plant is significantly *less* likely to suspend an investment project when other plants suspend theirs. This suggests that firms investing in standard technology engage in a war-of-attrition game, in which suspensions by others increase the expected payoff from the firm's own investment. By contrast, suspensions at other plants significantly *increase* the probability that a new technology plant will suspend its own project. This finding suggests that a clustering of actions due to social learning is more likely to occur among the new technology plants, perhaps because these plants face greater uncertainty, since they are uncertain about demand conditions and the costs of using the new technology.

For both standard and new technology semiconductor plants in this study, the behaviour of others had a significant effect on each plant's own suspension decision. Theory implies that wars of attrition and clustering behaviour can cause inefficient delays, so social welfare is lower than if agents acted independently, rather than waiting for other suspensions. Resources may be wasted as firms continue investment projects longer than is socially optimal in the low-demand state. My findings imply that social learning may explain how large overcapacities can be built up in the semiconductor industry, and that, if a large number of the firms are adopting new technology, there is more likely to be an abrupt collapse in aggregate investment.

This paper is organized as follows. Section 2 reviews some of the related literature on social learning theory and empirical work. Section 3 provides an overview of the

3. The sample period covers the introduction of 12-inch wafer technology over the standard 8-inch size. This new technology significantly increases the production capacity of semiconductor plants.

theoretical model that underpins my empirical analysis. The data are described in section 4. The empirical methodology is explained in section 5 and the results are reported in section 6. Section 7 concludes.

2. Related Literature

Chamley (2004) provides an excellent recent text on social learning with rational agents. In this section, I provide a brief survey of literature closely related to the model developed by CL94, which forms the theoretical basis for my empirical work. CL94 build an (S, s)-type model of irreversible investment, in which fixed adjustment costs lead firms to choose only infrequently when to switch from inertia to action (suspending their investment project).[4] Agents try to predict demand at the time the investment project will be completed, based on their own private information about demand, creating the possibility for social learning from other agents' suspensions. Project suspensions cause previously disparate, heterogeneous, private information to be aggregated by the market, and may lead to significant changes in overall beliefs and, potentially, a collapse in aggregate investment.

Several early models of irreversible investment with uncertainty and learning, such as those developed by Zeira (1987, 1994), Demers (1991), Rob (1991), and Caplin and Leahy (1993), assume that 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 feature heterogeneous beliefs and generate discontinuous investment patterns, whereby aggregate investment can collapse suddenly after the first suspensions, as other agents learn that demand is low.

In the CL94 model, when demand is low suspensions are delayed longer than they would be in an equilibrium of full information-sharing. The delay occurs because, rather than

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

acting independently, firms may wait to see whether other firms suspend. Resources can be wasted by continuing projects when demand is low, which results 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 those developed by Romer (1993), Bulow and Klemperer (1994), and Chamley and Gale (1994), allow heterogeneity, but take the differences in beliefs as given, whereas CL94 allow agents' beliefs to evolve. More similar to CL94 are the early theories of information cascades developed first by Banerjee (1992), Bikhchandani, Hirschleifer, and Welch (1992, 1998), 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 CL94 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) (CL98), and Hovarth, Schivardi, and Woywode (2001). CL98 use a search framework to consider information aggregation and endogenous timing in the context of the decision on whether to enter a property market with uncertain demand. Their model also generates socially inefficient delay and a discontinuous pattern of activity. CL98 conclude that their model explains the observed behaviour of the retail property boom in New York in the 1990s. Hovarth, Schivardi, and Woywode (2001) develop a model of social learning and firm entry and exit, similar to that developed by CL94. Their model can generate either discontinuous or gradual patterns of entry, depending on the assumptions of how uncertainty is resolved. They find that 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 United States in the late nineteenth and early twentieth centuries.

2.1 Empirical literature

Brock and Durlauf (2001) discuss some applications of social learning models, and examine the main econometric problems involved in estimating them. Most empirical studies of social learning focus on individual behaviour. Although social learning models often examine investment decisions, few authors test social learning theories empirically with data on firms. Therefore, this study helps to develop the empirical literature on social learning.[5]

Two recent studies of technology adoption and social learning, by Foster and Rosenzweig (1995) and Munshi (2004), test for social 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 the behaviour of his or her neighbours. Foster and Rosenzweig find that learning from the experiences of neighbours 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 the effects of social learning are stronger when agents' characteristics are more homogeneous, and, conversely, that social learning is weaker in a heterogeneous population. Miguel and Kramer (2003) study an unsuccessful attempt to convince individuals to adopt drug treatment in Kenya. Their findings are interesting because social learning had a significant effect on the *non-adoption* of technology.

Guiso and Schivardi (2000) study the labour force adjustment decisions of firms and the influence of social learning. Using employment data from manufacturing firms in Italy,

---

5. The literature on social learning and investment discussed in this paper constitutes a relatively small part of the literature on social interactions, and is related to the social capital literature. Models of social interactions have a wide range of applications. Some of the most active areas of research thus far are: neighbourhood influences on socioeconomic outcomes, such as education attainment, income, and labour force participation; spatial agglomeration; technology choices; interdependent preferences; and anti-social behaviour. See Brock and Durlauf (2001) for references.

they find that the actions of similar neighbouring firms significantly affect the labour force adjustment of a firm, but that the actions of dissimilar or non-neighbouring firms have no influence. Guiso and Schivardi's results imply that social learning is a significant factor in explaining the employment adjustment behaviour of firms that are 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 do larger firms.

3. The Theoretical Framework

CL94 model a firm's decision to continue or to suspend an investment project that takes time to build. Firms are assumed to be risk-neutral and small relative to the whole market, taking prices as given and maximizing the expected value of profits. During the life of the project, each firm gathers information on the state of final demand and then decides in each period whether to continue, temporarily suspend, reactivate, or cancel the project. The choices depend on the firm's perception of the true state of demand, which is either high or low. The firm pays an entry cost of $k > 1$ to initiate the investment. Continuing involves a cost per period assumed to be one, and the cost to suspend is assumed to be zero. Reactivating a suspended project involves an additional cost of $mk \in [1,\kappa]$.

Firms use three sources of information to form beliefs about what the state of demand will be for a project when it is completed. First, there is the ex ante common prior that demand in period T can be either high or low, with equal probability. Second, in each period, the firm receives private information in the form of a noisy signal, either "good" or "bad." The information content of a firm's private signals is reflected in variable $p \in [0.5, 1]$, the probability that a firm receives a good signal when demand is actually high. The third source of information is the firm's observations of the history of decisions made by all other firms regarding entry, continuation, suspension, reactivation, and cancellation. This information gained from observing others is the social learning aspect of the model. Each period, the firm updates its beliefs using Bayes' rule to incorporate the complete history of decisions made by other firms and the private signals it has received so far.

CL94 solve for the set of symmetric Nash equilibria in which all firms follow a strategy that is optimal, given the information revealed when others follow the same strategy. Note that, when all firms do the same thing, there is no release of new private information to other market participants. For example, if all firms continue, there is no way to tell which firms have received good or bad signals and there is no social learning. Once the first suspensions occur, however, the public information available to the market changes and social learning occurs.

A key feature of the CL94 model is that the timing of the first suspensions is endogenous, because the most pessimistic firms (those receiving an unbroken series of bad signals) will always be the first to suspend. The most pessimistic firms suspend first because they judge the cost of continuing to be greater than the option of delaying to learn more about demand conditions. Social learning occurs as follows. The remaining firms are less pessimistic, so they delay longer to learn more about the state of demand from the actions of others, hoping to avoid the cost of wrongly suspending their investment. Therefore, all the most pessimistic firms will suspend first in period t, and the remaining firms will wait until period $t + 1$ to learn from the first who suspended what the state of demand will be. If a high proportion of firms suspend in period t, the remaining firms will know there is a lot of pessimism and conclude that demand is low, so they will suspend en masse in period $t + 1$. If the proportion of the first to suspend is small, the remaining firms will conclude that demand is high and continue, while the suspended firms will reactivate their projects and incur a re-entry cost, mk. Further details on the CL94 model are provided in the appendix.

Consistent with other models, CL94 predict that delays that arise from social learning reduce social welfare. Resources are wasted as agents continue projects in the low-demand state longer than they would have if they acted only on their own signals. Thus, it is important to determine whether social learning actually affects investment decisions in the semiconductor industry. If so, suspensions by other firms will increase the probability that a given firm will suspend its own project. If not, other suspensions will not be significant. The empirical methods used to test the hypothesis that arises from the model are explained in section 5.

4. Data Description

I use semiconductor plant-level data from a commercial database called World Fab Watch (WFW), produced by Strategic Marketing Associates, a research firm in the semiconductor industry based in Santa Cruz, California. WFW contains data on investments by semiconductor firms 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 e-mail enquiries. Strategic Marketing Associates estimate that the database covers more than 95 per cent 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 the total expected cost of the project, broken down into construction costs and equipment 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 announced that it intends to build or upgrade a fabrication plant, but construction has not yet begun. I omit these projects because no initiation cost can actually be 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 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. For 23 investment projects, I obtain some data from news sources.

The period studied consists of 30 quarters from 1 January 1995 to 30 June 2002. This period was chosen 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 in which the activity occurred, I group the data into quarters, since some of the date variables (date of work commencement, production date, date of the delay announcement) come from news articles only, rather than from WFW itself. The dates of the news articles may be less precise than the dates contained in the original WFW database, so I attempt to identify only the quarter and year in which the activity for 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 the WFW database contains a date for the delay announcement and/or comments that note a delay in the project. 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 determine whether 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 this 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 quite lumpy pattern of initiations and suspensions of semiconductor plant investments. Suspensions are clustered into two periods: 1996Q2 to 1998Q4 and 2000Q4 to 2002Q1. During these two 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.[6] Over the period 1995Q1 to 2002Q2, there were fairly large fluctuations in shipments, especially in North America. These fluctuations roughly correspond to the pattern of project initiations in the sample of plants shown in Figure 1. Figures 1 and 2 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. The initiation cost is measured by the construction costs as a per cent of the total cost. The initiation cost averages 17.5 per cent of the total cost of the respective projects. The total cost averages $593 million (in 1996 U.S. 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 a given plant's own project (either through completion or suspension). For the average plant in the sample, 3.1 per cent 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 per cent 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 per cent.

Table 2 compares suspended and continued projects by region. Most of the investment activity over the whole period occurred in North America and Asia, excluding Japan (referred to herein as Asia Pacific). Of the 39 suspended projects, 12 were located in North America and 16 in Asia Pacific. Japan and Europe had five and six suspended

6. All sample data on costs and aggregate sales were originally in nominal U.S. dollars. Dollar values are converted to 1996 U.S. dollars using the U.S. GDP implicit price deflator, published in Table 7.1 on the Internet Web site for the Bureau of Economic Analysis (http://www.bea.doc.gov/), 31 October 2003.

projects, respectively. Suspended projects made up 15 per cent of all projects and 30 per cent of the total expected cost. Japan had the lowest percentage of projects suspended, and the rest of Asia Pacific had the highest percentage. Suspended projects are, on average, nearly twice as expensive as continued projects. The ratio of the total cost of suspended to continued projects ranged from a low of 0.15 in Japan to 0.58 for North America.

5. Empirical Methodology

The semiconductor dataset provides a good opportunity to test the CL94 model, because it allows one to observe firms that do suspend their projects and those that do not suspend them; the non-suspenders can act as a control group and mitigate problems of selection bias. The main test investigates whether the probability that a given firm will suspend its project depends on the proportion of other firms that suspended in the previous period.

I model individual behaviour as a binary choice, to suspend or not to suspend, using the probit model shown in equation (1). Note that the semiconductor data I use are plant level and the results reported in section 6 treat each plant as an individual decision-making agent. Grouping the observations by firm, however, does not change the results in any substantive ways.[7]

The regression model is:

$$\Pr(Y_{irs} = 1) = \Phi(c + a' X_i + b' Y_{-irs} + d' Z_{rs} + e_{irs}), \tag{1}$$

where Pr $(Y_{irs} = 1)$ is the probability of suspension by plant i in region r at time s, where s is the end of the project because of either suspension or completion. The suspension

7. The robustness of the results is checked by controlling for potential unobserved common characteristics at the firm level by using clustered standard errors in the regressions. In additional regressions, I use a random-effects panel estimator, which treats plants owned by the same firm as part of the same panel. These alternative regressions do not yield any substantial differences from the results reported in Tables 3 through 5.

dummy variable $Y_{irs} = 1$ if the plant chooses to suspend its project, and $Y_{irs} = 0$ if the plant completes its project. F 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, reactivation cost, and 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 cost. Private signal quality is operationalized by the total expected cost of the project; this assumes that there may be a fixed cost to acquiring good information, and plants that can undertake more expensive projects are assumed to be able to gather better-quality information. In all cases, data for the expected cost are taken from announcements made at the beginning of the project. Differences in technology are proxied by the size of the semiconductor wafers to be manufactured at the plant. Larger wafer sizes are usually associated with newer technology.

The social learning effect is captured through the variable Y_{-irs}, which is the percentage of other active plants in region *r* that have been suspended in period *s*, where *s* 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 *s*. In the CL94 model, other suspensions in the *previous* period would influence the current period's suspensions; however, with quarterly data it seems more likely that a firm reacts to the behaviour of others in the same period. To check the validity of this intuition, I test the sensitivity of the results to the timing of the social learning variable by using suspensions of projects by others in the previous quarter only, and in the previous and current quarter.[8] There are no substantial differences in the results.

Z_{rs} is a vector of contextual regressors for region *r* in period *s* intended to capture the effect of common shocks and the influence of a common environment. In particular, Z_{rs} includes the percentage change in regional semiconductor sales from the previous quarter

8. In separate regressions, not shown.

or year, and a full set of year dummies interacted with a region. This is an attempt to control for regional factors, such as the Asian crisis, that may have affected the ability of some plants to acquire financing to complete their project.

5.1 Tests of the hypotheses

The key hypothesis test is that, if social learning is present, the coefficient on Y_{-irs}, ß, is positive, and if social learning does not affect the individual plant's suspension decision, then ß equals zero. The CL94 model also generates testable hypotheses in the form of sign predictions for the X_i variables. CL94 work out the comparative static effects of changes in the exogenous variables on the lower and upper limit of the first suspension times (see equations (A2) and (A3) in the appendix). To facilitate empirical tests using a probit model, I interpret the comparative statics of CL94 in terms of whether a change in the exogenous variable increases or decreases the probability that an individual project will be suspended.

CL94 show that increases in the initiation cost, *k*, reduce the set of equilibria that involve suspensions and thus reduce the probability that a given firm will suspend its project. I therefore expect the a coefficients on the initiation cost to have negative coefficients. An increase in initiation costs increases expected costs and raises the price of the good in the high-demand state. It then takes more bad news to convince the firm to suspend its project, which pushes back the first suspensions and reduces the number of suspensions that are likely to be observed.

Increases in the quality of the firm's private signals (p) are summarized as follows by CL94 (p. 559): "the more convincing is each individual signal, the fewer signals a firm needs to justify suspension." Better-quality private information decreases both the lower and upper bounds on equilibrium suspension times, which implies that suspensions occur sooner in the project, reducing the delay caused by social learning and making it more likely that one will observe suspensions in the low-demand state. Higher-quality private signals should also result in less reliance on social learning. Therefore, suspensions of projects by other firms are expected to have less influence on firms that have good private information.[9]

CL94 also consider some extensions to their model that are relevant to this study. In the basic model, all uncertainty is resolved by the first suspensions, but CL94 demonstrate that social learning will also occur in a more realistic setting, where uncertainty is not resolved until the project is completed. When the first firms suspend, others observe their actions and update their beliefs, causing some to suspend and others to continue. The firms that continue again gather private information until the suspension, and the market again aggregates the information and updates beliefs. Agents still learn from observing others and their own private information, but the social learning occurs in several stages, and suspensions are clustered in several distinct periods, rather than in the single cluster of the basic model. This extension does not imply any differences for hypothesis testing.

The basic model assumes a continuum of competitive firms, but CL94 also discuss the implications of a market that has a few firms acting strategically. One result is that firms will want to continue even when their signals are bad, to gain a larger share of the market. CL94 argue that this kind of “war-of-attrition” game further delays the first suspensions, and reduces the probability of suspensions in their model. However, other models that consider wars of attrition in more detail emphasize not only the delays but also that payoffs of firms will be strategic substitutes, such that a given firm’s expected profits will increase when other firms suspend their investment project. This may imply a negative and significant relationship between suspensions made by other firms and a firm’s own probability of suspension.[10] A second implication of an imperfectly competitive market structure is that the continuation of investment projects by other firms

9. The model also predicts that an increase in the cost of reactivation, *m*, decreases the set of equilibrium suspension times and reduces the probability of observing a suspension for a given firm. The database does not include a variable on reactivation costs, so this prediction is not tested.

10. See Chamley (2004, 288).

conveys a positive signal, encouraging others to enter the market, or to continue in it. This hypothesis is left for future work.

5.2 Identification

Manski (1993, 2000) points out that an important problem in identifying the parameters of social effects arises when social learning models are being estimated: reference group determinants and individual determinants of an individual agent's 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 (1993, 532) 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."

Brock and Durlauf (2001) analyze the identification problem in social interaction models. They show (p. 3322) 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 non-linear function of the contextual effects. I use these criteria to verify whether the model in equation (1) is identified.

Defining appropriate reference groups is often difficult in studies of social learning: it requires knowledge of information flows between agents. Since semiconductor plants are often located in different countries or even different continents than their headquarters, it is not obvious what the appropriate reference group should be. Initially, I treat the whole industry as operating in one reference group; i.e., all fabrication plants in the industry.

This seems plausible, given the global nature of the industry, and the fact that firms can easily learn about other fabs investment behaviour by purchasing the database I use. I also consider social effects that arise between firms located in the same broad region; hence, for some regressions, plants are grouped with other plants to form four regional reference groups: Europe, North America, Japan, and Asia Pacific. The relatively small number of observations in the database does not allow smaller groupings.

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_{rs}. 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_{rs} 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_{rs} variables.

It is possible, however, that a linear relationship exists between the average group behaviour, Y_{-irs}, and the contextual effects, Z_{rs}, since both are measured at time s 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 (1993, 2000). However, if the other suspensions variable, Y_{-irs}, is a *non-linear* function of the contextual effects, Z_{rs}, the model should be identified based on Brock and Durlauf's criteria. I use a RESET (omitted variable) test for non-linearity between these variables, as recommended by Davidson and MacKinnon (1993, 195).

When the whole database is treated as one group, the RESET test regresses the percentage of other projects suspended during the quarter when the plant's own project ended (Y_{-is}) 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, are 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 that have regional variables are 0.001 and 0.003. Both sets of test results show that one cannot reject the hypothesis that higher-order effects are significantly different from zero, which implies that a *non-linear* rather than a linear relationship exists between the average group behaviour and the contextual regressors. These results suggest that the model in equation (1) should be sufficient to identify the social learning effects via the coefficient estimate for other suspensions, Y_{-irs}.

6. Results

6.1 Estimates of social learning in suspension decisions at semiconductor plants

Table 3 reports the results of estimating the basic model in equation (1) using probit regressions. The specifications in columns 1 and 2 assume that 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, which tests whether those plants rely less on social learning, assuming they have better-quality information, as hypothesized in the CL94 model. Large plants are those that have a total cost greater than the median plant in the sample.

The variables that measure the characteristics (X_i) of the plant's own investment project all have the expected signs, and are significant at the 1 per cent level in all but two cases. Projects that have a higher initiation cost as a share of the total cost 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 the plant's private information, this finding suggests that better-informed plants are more likely to suspend their projects. The finding is also consistent with the predictions of the CL94 model.[11] A plant that has good information is less likely to delay its decision to suspend (either to observe others or to gather more private information), and therefore a suspension is more likely to occur in that type of plant. 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.

The key hypotheses involve the coefficient on the behaviour of other plants (Y_{-irs}), measured as the percentage of active projects suspended at those plants in relation to a given plant's own suspension behaviour. The main finding from Table 3 is that *none* of the social learning variables, *OTHER SUSPENSIONS*, *OTHER REGIONAL SUSPENSIONS,* or *LARGE X OTHER SUSP.*, has the expected positive sign, and six of eight coefficients are not significant at the 5per cent level. To verify the timing of the social learning variable, I have included one-quarter lags of *OTHER SUSPENSIONS*$_{t-1}$, individually and in combination with the same quarter observation in additional regressions, not shown 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 a plant's decision to suspend its investment project. I test the robustness of this result by weighting the other suspensions by project cost, and by duration (Table 4). The results reinforce the findings of the basic model.

---

11. It may be possible that higher-cost projects are more poorly managed or face more severe financing constraints, and this could explain why they are more likely to be suspended. These hypotheses cannot be ruled out by this analysis, since I do not have data to control for them. Even if total cost is proxying for something other than signal quality, however, this should not affect this paper's examination of whether social learning plays a significant role in the suspension of projects. Therefore, the main findings of this paper should not be affected by these hypotheses.

The regional social learning effects, shown in Table 3, are negative and significant, which is somewhat puzzling. They signify that other suspensions in the same region reduce the probability that a given firm will suspend its project. CL94 suggest that, if firms behave strategically, a “war-of-attrition” scenario may occur: firms will continue even when their signals are bad, hoping others will suspend, making the market more profitable for the remaining firms. This possibility can 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 of Table 3 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.* will be significantly smaller than the coefficient on *OTHER SUSPENSIONS*. However, a statistical test that shows that the two coefficients are equal cannot be rejected, which implies that there is no significant difference between large and small plants with respect to social learning.[12] In particular, other suspensions do not significantly influence a 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 that of others. Weighting the other suspensions in some way may reveal social learning effects not present in the basic regression models. I weight the other suspensions in two different ways: by total cost and by duration.

Table 4 shows 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* shows simply the

---

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

dollar value of other suspended projects based on total cost. Column 2 shows only other suspensions that have a total cost greater than the median value, to capture possible non-linear effects, so 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 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 per cent level. Column 4 uses the duration of the suspended projects to weight their possible influence. CL94 (p. 562) argue that "the probability other firms have received good signals will grow, the longer they remain in the market." 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. Weighting the other suspensions by their duration, however, still does not change the finding that social learning does not appear to significantly influence 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 the semiconductor 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 switch from the previous standard of 8-inch wafers was a significant technological change that required 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. A small-scale 12-inch wafer plant, built for research and development purposes, was completed in 1997, and the first commercial production plant was completed in 1999. Of the 28 plants that were to use the 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 to form beliefs not only about demand conditions, but also about the optimal time to adopt a new technology. This is not just a technological or research and development spillover. It is not necessary to transfer between semiconductor firms any technical knowledge about how to manufacture 12-inch wafers. Instead, social learning theories imply that there is an information spillover whereby a firm learns about the potential profitability of investing in the new technology simply by observing whether other firms continue their investment project.

Table 5 shows the results of regressions testing for social learning by firms that adopted this new technology. To do so, a dummy variable that identifies 12-inch wafers is 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 3 and 4 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, which indicates that the intercept term does not differ between 12-inch fabs and other plants. I therefore focus on the two interactions terms.

The main result is that the coefficient on the interaction variables for other suspensions interacted with the 12-inch dummy variable is positive and significant at the 5 per cent level in all four regressions. Thus, firms that attempted to adopt the 12-inch wafer technology were significantly more likely to suspend their new plant if any other projects had been suspended. Interestingly, the other plants—those using the conventional, smaller wafers—were much *less* likely to suspend their plant if there was another suspension, as shown by the significant but negative coefficients on the *OTHER SUSPENSIONS* and *OTHER REGIONAL SUSP.* variables.

First, 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 new wafer plants would be suspended. The other suspensions are not only plants that use 12-inch wafers; they may use any wafer size. When I treat the world as one region, the *OTHER SUSP. X 12 INCH WAFERS DUMMY* has a coefficient of 0.29 in 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 per cent increase in the number of other plant suspensions (anywhere in the world) increases the probability of suspension for a given plant by 3.6 per cent. If I consider only 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 per cent 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 per cent. Therefore, the economic significance of these findings is not large, but they do suggest that social learning may be more important for agents who face greater uncertainty. Another possible explanation is that, when a firm decides to adopt an unknown new technology, the quality of its private information is effectively lower than when it decides to suspend a project that uses a known technology.

Another interesting result from the technology choice regressions is that the firms using conventional technology behave differently from those that are adopting the new technology. Specifically, the negative and significant coefficients on the *OTHER SUSPENSIONS* and *OTHER REGIONAL SUSP.* variables show 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 per cent increase in the number of suspensions by other firms reduces the probability of suspension for the average firm by 1.4 per cent. For the *OTHER REGIONAL SUSP.* variable, the coefficients in columns 3 and 4 imply that a 1 per cent increase in other suspensions in the same region reduces the probability that the average firm will suspend their project by 1.1 to 1.2 per cent.

One explanation for the negative relationship between suspensions by others and suspension by a given conventional technology plant is that the given plant bases its decision more on a war-of-attrition game than on learning from others. Since it knows what to expect with respect to output and costs with the existing technology, its suspension decision may be to continue when rivals suspend because that decision will allow it to capture a larger share of the market. By contrast, when a firm is adopting a new technology, it faces more uncertainty concerning costs, output, productivity, and ultimately profits that will be generated by the new plant. Its decision to suspend is therefore more sensitive to worries that demand is weakening: it is more likely to suspend if a rival firm stops building a new plant.

6.3 Robustness to alternative specification of sales shocks

The preceding analysis assumes that aggregate demand shocks can be approximated by sales-growth variables measured using the percentage change in the aggregate worldwide (or regional) shipments value from the previous year or quarter. Since many of the changes in sales may be forecastable by semiconductor plants, their decision to suspend or continue their investment project may depend more on unexpected shocks to sales. An alternative method that reflects this possibility is to forecast aggregate sales and use the residuals from the forecast regression to represent aggregate sales shocks. The forecast regression uses ordinary least squares (OLS) to estimate the AR(4) model shown in equation (2). Since the data are quarterly, four lags of aggregate sales enter the forecast equation[13]:

$$SALES_t = SALES_{t-1} + SALES_{t-2} + SALES_{t-3} + SALES_{t-4} + u \ . \qquad (2)$$

The regression residuals from equation (2) are used in the probit regressions as a Z_t regressor, called *AGGREGATE SALES SHOCK*, in place of the aggregate sales-growth

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

variables. Table 6 reports the results of the probit regressions of the basic model and the model of the 12-inch wafer technology choice using the aggregate sales-shock variable. The basic model is shown in column 1 and the model of the technology choice is shown in column 2. 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, whereas the firms adopting the 12-inch wafer technology are positively and significantly affected by the suspensions of other projects.

7. Conclusions

The results of my research indicate that a semiconductor plant's decision to continue or suspend an investment project is significantly influenced by the suspension decisions made by similar plants in the industry, but that social interactions differ between plants investing in new technology as opposed to conventional technology. When investing in a major new technology, social learning as described in CL94 does seem to occur. Plants adopting a new generation of wafer technology are significantly more likely to suspend their project if other suspensions occur in the same period, which suggests that plants delay their own suspensions to learn from others about demand conditions or the cost of using the new technology, or both. This may explain the clustering of suspension and investment activity that occurs in this industry.

Plants adopting conventional technologies are not positively influenced by the behaviour of others; conversely, suspensions by others significantly *reduce* the probability that these plants will suspend their investment projects. These plants may expect to gain a larger share of the market by continuing to invest, in the hope that rivals will drop out. This suggests that plants investing in standard technology engage in a war-of-attrition game, in which suspensions by others increase the firm's expectations about the payoff from its own investment. The effect of the behaviour of others, however, is smaller for the conventional technology plants than for those adopting the new technology. These findings may indicate that social learning is associated with conditions where uncertainty is unusually high, as with the adoption of a new technology, or when an agent's own private information is not very good.

Social learning theories imply that both wars of attrition and clustering behaviour can cause inefficient delays, so social welfare is lower than if agents acted independently, rather than waiting for others to suspend their investment. Resources may be wasted as plants continue investment projects longer than is socially optimal in the low-demand state. My findings imply that social learning may explain how large overcapacities can be built up in the semiconductor industry, and, if a large share of the firms are investing in new technology, there is more likely to be an abrupt collapse in aggregate investment.

The results of my research are consistent with earlier work on technology adoption that find significant social learning effects in databases that feature relatively simple, non-capital-intensive technologies in agriculture. This paper has approached the question of social learning from the opposite direction, by considering when an investment project is suspended, thereby allowing me to compare plants that suspend their investment with a control group of plants that do not. Using data from a highly cyclical, capital-intensive industry with complex technologies, I have also found evidence that social learning influences decisions on technology adoption as well as strategic decisions. Further work is required to establish more generally the conditions under which agents rely on private information versus social learning.

References

Banerjee, A. 1992. "A Simple Model of Herd Behavior." *Quarterly Journal of Economics* 107(3): 797–817.

Bikhchandani, S., D. Hirschleifer, and I. Welch. 1992. "A Theory of Fads, Fashion, Custom and Cultural Change as Information Cascades." *Journal of Political Economy* 105(5): 992–1026.

———. 1998. "Learning from the Behaviour of Others: Conformity, Fads, and Information Cascades." *Journal of Economic Perspectives* 12(3): 151–70.

Blinder, A. 1981. "Retail Inventory Behavior and Business Fluctuations." *Brookings Papers on Economic Activity* 2: 443–505.

Brock, W.A. and S.N. Durlauf. 2001. "Interactions-Based Models." In *Handbook of Econometrics*, edited by J. Heckman and E. Leamer, Vol. 5. Amsterdam: North Holland.

Bulow, J. and P. Klemperer. 1994. "Rational Frenzies and Crashes." *Journal of Political Economy* 102(1): 1–23.

Caballero, R.J. 1999. "Aggregate Investment." In *Handbook of Macroeconomics,* edited by J.B. Taylor and M. Woodford, Vol. 1. Amsterdam: Elsevier Science.

Caballero, R.J. and E. Engel. 1991. "Dynamic (S, s) Economies." *Econometrica* 59(6): 1659–86.

Caplin, A. 1985. "The Variability of Aggregate Demand with (S, s) Inventory Policies." *Econometrica* 53(6): 1395–1409.

Caplin, A. and J. Leahy. 1993. "Sectoral Shocks, Learning and Aggregate Fluctuations." *Quarterly Journal of Economics* 60(4): 777–94.

———. 1994. "Business As Usual, Market Crashes and Wisdom After the Fact." *American Economic Review* 84(3): 548–65.

———. 1998. "Miracle on Sixth Avenue: Information Externalities and Search." *Economic Journal* 108(1): 60–74.

Caplin, A. and D. Spulber. 1987. "Menu Costs and the Neutrality of Money." *Quarterly Journal of Economics* 102(4): 703–25.

Chamley, C. 2004. *Rational Herds: Economic Models of Social Learning.* New York: Cambridge University Press.

Chamley, C. and D. Gale. 1994. “Information Revelation and Strategic Delay in a Model of Investment.” *Econometrica* 62(5): 1065–85.

Davidson, R. and J.G. MacKinnon. 1993. *Estimation and Inference in Econometrics*. New York: Oxford University Press.

Demers, M. 1991. “Investment Under Uncertainty, Irreversibility and the Arrival of Information Over Time.” *Review of Economic Studies* 58: 333–50.

Foster, A.D. and M.R. Rosenzweig. 1995. “Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture.” *Journal of Political Economy* 103(5): 1176–1209.

Gale, D. 1996. “What Have We Learned from Social Learning?” *European Economic Review* 40: 617–28.

Guiso, L. and F. Schivardi. 2000. “Information Spillovers and Factor Adjustment.” Bank of Italy Discussion Paper No. 368.

Hovarth, M., F. Schivardi, and M. Woywode. 2001. “On Industry Life-Cycles: Delay, Entry and Shakeout in Beer Brewing.” *International Journal of Industrial Organization* 19: 1023–52.

Lee, I.H. 1992. “Market Crashes and Information Cascades.” UCLA Graduate School of Management. Photocopy.

Manski, C. 1993. “Identification of Endogenous Social Effects.” *Review of Economic Studies* 58(3): 531–42.

———. 2000. “Economic Analysis of Social Interactions.” *Journal of Economic Perspectives* 14(3): 115–36.

Miguel, E. and M. Kramer. 2003. “Networks, Social Learning and Technology Adoption: The Case of Deworming Drugs in Kenya.” Photocopy.

Munshi, K. 2004. “Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution.” *Journal of Development Economics* 73(1): 185–213.

Rob, R. 1991. “Learning and Capacity Expansion under Demand Uncertainty.” *Review of Economic Studies* 58(4): 655–75.

Romer, D. 1993. “Rational Asset Price Movement without News About Fundamentals.” *American Economic Review* 83(5): 1112–30.

Welch, I. 1992. “Sequential Sales, Learning and Cascades.” *Journal of Finance* 47(2): 695–732.

Zeira, J. 1987. “Investment as a Process of Search.” *Journal of Political Economy* 95(1): 204–10.

———. 1994. “Information Cycles.” *Review of Economic Studies* 61: 31–44.

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) / Σ TC (Continued)	0.48	0.54	0.14	0.58	0.44

Table 3: Probit Regressions for Basic Models
(dependent variable is suspension = (1,0))

	1	2	3	4	5	6
INITIATION COST (%)	-0.0577	-0.0587	-0.0615	-0.0641	-0.0692	-0.0703
	-(3.70)	-(3.59)	-(3.65)	-(3.50)	-(3.74)	(0.00)
TOTAL COST ($)	0.0012	0.0012	0.0008	0.0008	0.0019	0.0019
	(4.09)	(4.01)	(2.69)	(2.59)	(4.63)	(0.00)
WAFER SIZE	0.1981	0.1900	0.3428	0.3357	0.2532	0.2615
	(2.39)	(2.26)	(3.32)	(3.37)	(1.08)	(0.28)
OTHER SUSPENSIONS (%)	-0.0268	-0.0376			-0.0113	-0.0165
	-(0.54)	-(0.79)			-(0.14)	(0.84)
OTHER REGIONAL SUSP. (%)			-0.0732	-0.0876		
			-(2.26)	-(2.86)		
LARGE X OTHER SUSP. (%)					-0.1453	-0.1443
					-(1.76)	0.0750
AGG. SALES GROWTH (%)	0.0006				-0.0109	
(annual)	(0.05)				-(0.60)	
AGG. SALES GROWTH (%)		-0.0175				-0.0004
(quarterly)		-(0.86)				(0.98)
REGIONAL SALES GROWTH (%)			0.0043			
(annual)			(0.28)			
REGIONAL SALES GROWTH (%)				-0.0276		
(quarterly)				-(1.16)		
N	227	227	180	180	200	200
Wald chi2	37.96	41.28	75.95*	77.61*	59.95	59.72
Pr > chi2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R2	0.3638	0.3673	0.4216	0.4308	0.3946	0.3914

Notes: Coefficients are shown with *t*-statistics 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 the U.S. GDP deflator. All regressions use robust standard errors. Columns 5 and 6 exclude plants with 12-inch wafer technology. In columns 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. *Wald statistics could not be calculated in the regional model with robust standard errors, probably because there are too few observations. The value reported is the chi-square statistic for the regression estimated without robust standard errors.

Table 4: Probit Regressions with Weighted Other Suspensions (dependent variable is suspension = (1,0))

	1	2	3	4
INITIATION COST (%)	-0.0592	-0.0594	-0.0590	-0.0595
	-(3.63)	-(3.65)	-(3.61)	-(3.68)
TOTAL COST	0.0012	0.0012	0.0012	0.0012
	(3.93)	(3.93)	(3.95)	(4.07)
WAFER SIZE	0.1906	0.1905	0.1920	0.1918
	(2.24)	(2.24)	(2.26)	(2.27)
OTHER SUSPENSIONS (Wgt $)	-0.0001			
	-(1.01)			
OTHER SUSPENSIONS (%)			-0.0193	
($ value as % of other active)			-(0.86)	
OTHER LARGE SUSP. ($)		-0.0001		
		-(1.12)		
DURATION OTHER SUSP.				-0.0267
(quarters)				-(1.40)
AGG. SALES GROWTH (%)	-0.0240	-0.0255	-0.0193	-0.0235
(quarterly)	-(1.08)	-(1.13)	-(0.90)	-(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

Notes: Coefficients are shown with *z*-statistics 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 the 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 column 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	-0.0588	-0.0551	-0.0581
	-(3.72)	-(3.61)	-(3.21)	-(3.07)
TOTAL COST	0.0014	0.0013	0.0013	0.0013
	(4.72)	(4.64)	(4.91)	(4.70)
12 INCH WAFERS DUMMY	-0.3888	-0.4087	0.1057	0.1653
	-(0.64)	-(0.72)	(0.15)	(0.25)
OTHER SUSPENSIONS (%)	-0.1000	-0.1121		
	-(1.74)	-(2.01)		
OTHER SUSP. X 12 INCH WAFERS DUMMY	0.2913	0.2921		
	(2.79)	(2.95)		
OTHER REGIONAL SUSP. (%)			-0.1000	-0.1155
			-(2.98)	-(3.34)
OTHER REGIONAL SUSP. X 12 INCH DUMMY			0.1636	0.1574
			(2.06)	(2.08)
AGG. SALES GROWTH (%)	-0.0017			
(annual)	-(0.13)			
AGG. SALES GROWTH (%)		-0.0187		
(quarterly)		-(0.96)		
REGIONAL SALES GROWTH (%)			0.0058	
(annual)			(0.41)	
REGIONAL SALES GROWTH (%)				-0.0286
(quarterly)				-(1.18)
N	227	227	180	180
Wald chi2	37.36	38.28	76.27*	77.93*
Pr > chi2	0.0001	0.0001	0.0000	0.0000
Pseudo R2	0.3928	0.3967	0.4234	0.4326

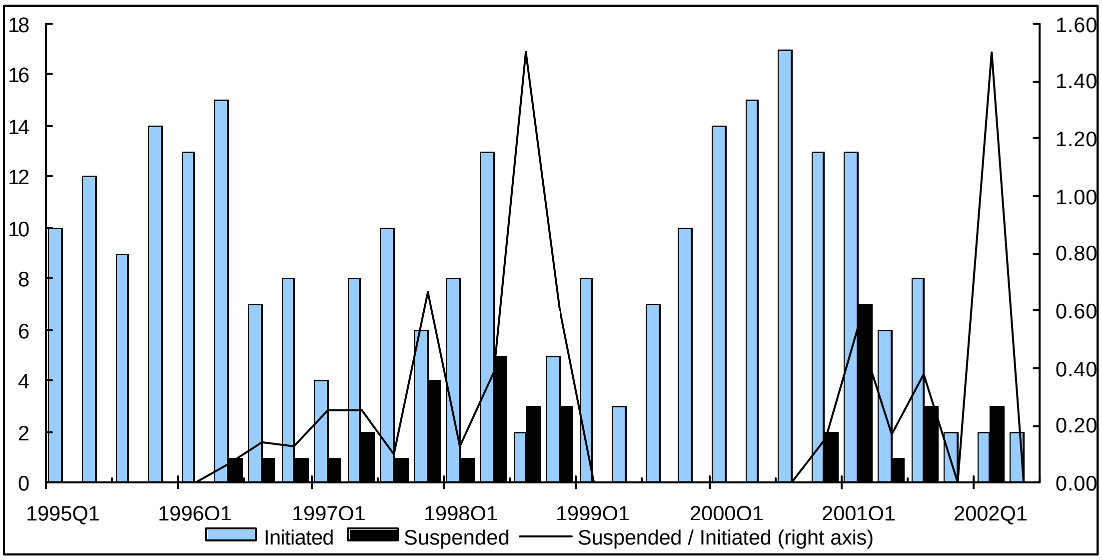
Notes: See notes to Table 3. *Wald statistics could not be calculated in the regional model with robust standard errors, probably because there are too few observations. The value reported is the chi-square statistic for the regression estimated without robust standard errors.

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

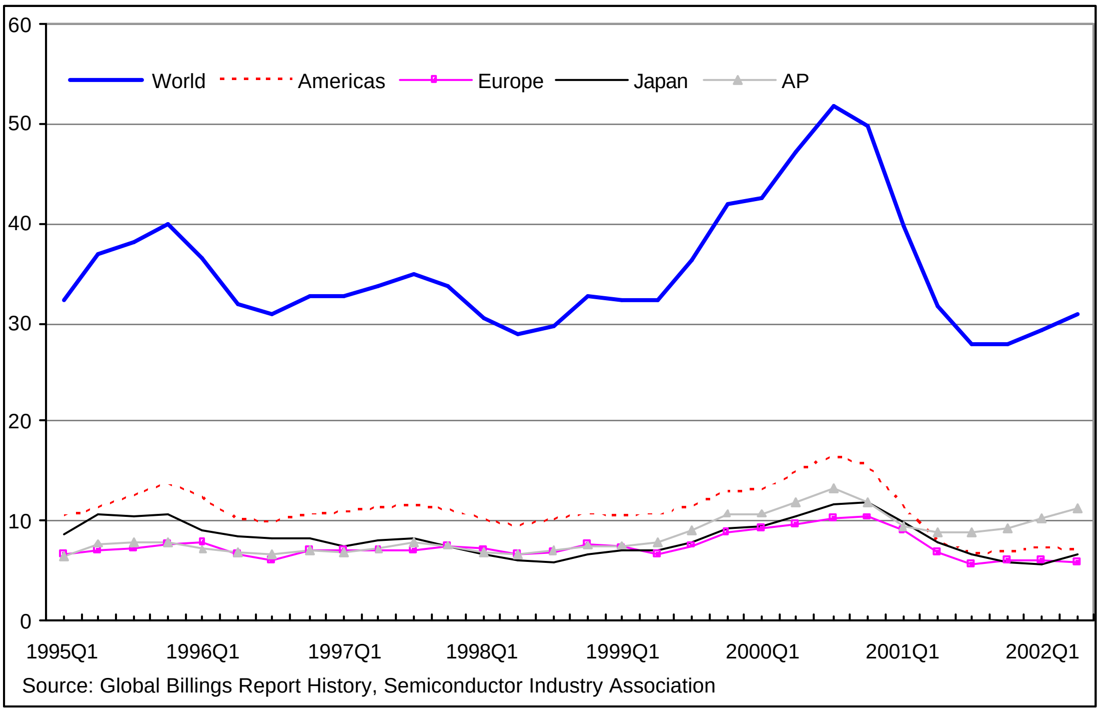
Notes: Coefficients are shown with *z*-statistics in parentheses. All regressions include a constant and year dummies. Year or quarter refers to the period when the project was completed or suspended. Dollar values are in 1996 U.S. dollars, converted from nominal dollars using the U.S. GDP deflator.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

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



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

Figure 2: Semiconconductor Shipments Per Quarter, Worldwide (1996 U.S. dollars, billions)



Appendix: Detailed Summary of Caplin and Leahy (1994) Model

CL94 model a firm's decision to suspend an irreversible investment that takes T periods to build. The firm pays an entry cost of $k > 1$ to begin and decides in each period whether to continue, temporarily suspend, reactivate, or cancel the project. To continue involves a cost per period assumed to be one, and the cost to suspend is assumed to be zero. Reactivation after suspension involves an additional cost of $mk \in [1, \kappa]$. The firm's choices depend on its perception of the true state of demand when the project is completed, 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; if demand is low, the firm sells nothing and has no revenue.

A firm's beliefs about the state of demand in period T are formed from three sources of information. First, there is the ex ante common prior that demand in period T can be either high or low, with equal probability. Second, each firm receives private information in the form of a noisy signal (either "good" or "bad") in each period that its project is active. Regarding the information content, or quality, of the firm's private signals, the variable $p \in [0.5,1]$ indicates the probability that it will receive a good signal when demand is actually high, and $1 - p$ indicates the probability that it will receive a bad signal when demand is high. The probability that the firm will receive a good signal when demand is actually low is q, and the probability that it will receive a bad signal when demand is low is $1 - q$. The signals are assumed to be symmetric, such that $q = 1 - p$. The signals are also assumed to be conditionally independent over time and across firms, given the true state of demand.

The third source of information is the firm's observations of the history of decisions by all other firms regarding entry, continuation, suspension, reactivation, and cancellation. The information gained from observing others is the social learning aspect of the model. Each period, the firm updates its beliefs about the state of demand at the end of the project using Bayes' rule to incorporate the complete history of decisions made by other firms through to the end of the previous period, and the string of private signals it has received so far.

CL94 define a symmetric Nash equilibrium as a strategy *p(c,z)*, such that *p* is optimal and uses all the information revealed when other firms also play *p* and there are *E* entrants, and the ex ante expected profits are zero. The strategy *p(c,z)* consists of the probability of continuing $c(I_s) \in [0,1]$, and the probability of reactivating if suspended, $z(I_s) \in [0,1]$, where I_s is the firm's information set in period *s*. I_s consists of the firm's private signals through period *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, *k*; the reactivation cost, *mk*; and the information content of each signal, *p*.

If there were complete information, firms would enter in period zero, observe other firms' private signals in period one, and immediately know the true demand state. They would then either continue through to period *T* or exit in period one, and all uncertainty about demand would be resolved. In CL94, the state of demand is not known until some firms reveal their private information by suspending. Therefore, a private information phase covers periods $1 = s = t-1$, where $t < T$ is the time of the first suspensions. In the private information phase, all firms gather their own private information and continue their project. In period *t*, some firms suspend their project, based on their private signals. In the basic model, these first suspensions have no social learning component; these agents act independently of the behaviour of others.

CL94 prove that 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 in which 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.[1] If the proportion of firms that suspend is high, then demand is low, and vice versa. Social learning occurs in period $s > t$, when all firms have observed the period t suspensions and know the state of demand based on the behaviour of the first firms to suspend. They continue or reactivate (if they suspended in t) if demand is high, and they exit if demand is low.

The critical result in CL94 is to identify t, the time of the first suspensions. Formally, CL94 find the equilibria by determining whether some arbitrary period, t, is a first-suspension time, by solving:

$$t = \min_{s} \left\{ s \in [1, T] : c(I_s) < 1 \text{ for some } I_s \in \Omega_s(E) \right\}, \tag{A1}$$

where O_s is the set of all information sets corresponding to the set of firms entering, E. The set of possible equilibrium first-suspension times is identified by finding the upper- and lower-bound conditions for period t.

The lower bound on the first-suspension time, T_L, is the earliest period in which suspensions can occur. The firm's beliefs about the probability of demand being high are assumed to increase strictly according to the number of good signals that it receives. Firms with the fewest good signals are the most pessimistic about the state of demand, and they suspend first. To find the earliest suspension time, CL94 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

1. This rather strong result from the basic model is weakened in extensions to it, without changing its predictions.

cost of having to reactivate if demand turns out to be high. This reasoning generates a condition for the lower-bound T_L on the first suspension period:

$$T_L: \quad mk = \left(\frac{p}{q}\right)^t. \tag{A2}$$

Equation (A1) shows that the first suspensions must occur late enough that the most pessimistic firms are willing to suspend their project and reveal their private information. That is, the expected value of continuing must be non-negative for all periods before t for all firms, even for a firm with no good signals; otherwise, the firm would suspend before period t. This condition, and the free-entry condition that expected profits are zero, allow CL94 to find an upper bound on the earliest suspension time, T_U, in which $U(s,t) \geq 0$ for all periods $s \in [1, t\text{-}1]$, 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:

$$T_U: \quad U(s,t) \geq 0, \text{ where}$$

$$\begin{aligned} U(s,t) = \frac{q^s}{p^s + q^s}[P_H - T - (t-1)] - (t-s) - mk \Pr_s(\{h(s_t) \leq h^*\} \cap \{H\}) \\ - \Pr_s(\{h(s_t) > h^*\} \cap \{L\}) \end{aligned} \tag{A3}$$

and where H and L denote the high- and low-demand states, respectively. The first term is the expected revenue less continuation costs that the firm pays 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 reactivate if the firm wrongly suspends in period t. The fourth term is the probability that the firm pays the continuation costs in period t when demand is actually low. This upper bound on t shows that, since firms pay a continuation cost for every active period, firms that believe demand is low would rather not pay further costs.

Bank of Canada Working Papers
Documents de travail de la Banque du Canada

Working papers are generally published in the language of the author, with an abstract in both official languages. ***Les documents de travail sont publiés généralement dans la langue utilisée par les auteurs; ils sont cependant précédés d'un résumé bilingue*.**

2004

2004-31	The New Keynesian Hybrid Phillips Curve: An Assessment of Competing Specifications for the United States	D. Dupuis
2004-30	The New Basel Capital Accord and the Cyclical Behaviour of Bank Capital	M. Illing and G. Paulin
2004-29	Uninsurable Investment Risks	C. Meh and V. Quadrini
2004-28	Monetary and Fiscal Policies in Canada: Some Interesting Principles for EMU?	V. Traclet
2004-27	Financial Market Imperfection, Overinvestment, and Speculative Precaution	C. Calmès
2004-26	Regulatory Changes and Financial Structure: The Case of Canada	C. Calmès
2004-25	Money Demand and Economic Uncertainty	J. Atta-Mensah
2004-24	Competition in Banking: A Review of the Literature	C.A. Northcott
2004-23	Convergence of Government Bond Yields in the Euro Zone: The Role of Policy Harmonization	D. Côté and C. Graham
2004-22	Financial Conditions Indexes for Canada	C. Gauthier, C. Graham, and Y. Liu
2004-21	Exchange Rate Pass-Through and the Inflation Environment in Industrialized Countries: An Empirical Investigation	J. Bailliu and E. Fujii
2004-20	Commodity-Linked Bonds: A Potential Means for Less-Developed Countries to Raise Foreign Capital	J. Atta-Mensah
2004-19	Translog ou Cobb-Douglas? Le rôle des durées d'utilisation des facteurs	E. Heyer, F. Pelgrin, and A. Sylvain
2004-18	When Bad Things Happen to Good Banks: Contagious Bank Runs and Currency Crises	R. Solomon
2004-17	International Cross-Listing and the Bonding Hypothesis	M. King and D. Segal
2004-16	The Effect of Economic News on Bond Market Liquidity	C. D'Souza and C. Gaa

Copies and a complete list of working papers are available from:
Pour obtenir des exemplaires et une liste complète des documents de travail, prière de s'adresser à :

Publications Distribution, Bank of Canada
234 Wellington Street, Ottawa, Ontario K1A 0G9
E-mail: publications@bankofcanada.ca
Web site: http://www.bankofcanada.ca

Diffusion des publications, Banque du Canada
234, rue Wellington, Ottawa (Ontario) K1A 0G9
Adresse électronique : publications@banquedducanada.ca
Site Web : http://www.banqueducanada.ca