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ESSAYS ON INVESTMENT FLUCTUATION AND MARKET  
VOLATILITY

by

Chaoqun Lai

A dissertation submitted in partial fulfillment  
of the requirements for the degree

of

DOCTOR OF PHILOSOPHY

in

Economics

Approved:

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Logan, Utah

2008

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## ABSTRACT

Essays on Investment Fluctuation and Market Volatility

by

Chaoqun Lai, Doctor of Philosophy

Utah State University, 2008

Major Professor: Dr. Terry Glover  
Department: Economics

This dissertation includes two different groups of objects in macroeconomics and financial economics. In macroeconomics, the aggregate investment fluctuation and its relation to an individual firm's behavior have been extensively studied for the past three decades. Most studies on the interdependence behavior of firms' investment focus on the key issue of separating a firm's reaction to others' behavior from reaction to common shocks. However, few researchers have addressed the issue of isolating this endogenous effect from a statistical and econometrical approach. The first essay starts with a comprehensive review of the investment fluctuation and firms' interdependence behavior, followed by an econometric model of lumpy investments and an analysis of the binary choice behavior of firms' investments. The last part of the first essay investigates the unique characteristics of the Italian economy and discusses the economic policy implications of our research findings.

We ask a similar question in the field of financial economics: Where does stock market volatility come from? The literature on the sources of such volatility is abundant. As a result of the availability of high-frequency financial data, attention has been increasingly directed at the modeling of intraday volatility of asset prices and returns. However, no empirical research of intraday volatility analysis has been applied at both a single stock level and industry level in the food industry.

The second essay is aimed at filling this gap by modeling and testing intraday volatility of asset prices and returns. It starts with a modified High Frequency Multiplicative Components GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model, which breaks daily volatility into three parts: daily volatility, deterministic intraday volatility, and stochastic intraday volatility. Then we apply this econometric model to a single firm as well as the whole food industry using the Trade and Quote Data and Center for Research in Security Prices data. This study finds that there is little connection between the intraday return and overnight return. There exists, however, strong evidence that the food recall announcements have negative impacts on asset returns of the associated publicly traded firms.

(104 pages)

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Chaoqun Lai

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## CHAPTER 1

## INTRODUCTION

Studies on the relation between aggregate fluctuation and individual behavior have expanded substantially during the past three decades. In macroeconomics, the literature in aggregate investment fluctuation is abundant, and so is the research on the sources of aggregate fluctuation and its link to individual firms' investment behavior. Most studies on investment interdependence behavior focus on the key issue of separating endogenous effects from exogenous shocks (Banerjee (1992), Brock and Durlauf (2001), Guiso and Schivardi (2008)). However, few researchers have addressed the issue of isolating the endogenous effects from a statistical and econometrical approach. The first essay of this dissertation presents a distributional test and an econometric model that investigates the amplification mechanism of aggregate investment fluctuation. We present empirical evidence that the fraction of firms that experience a large investment rate in the same region and industry is distributed exponentially. This finding questions the modeling strategy that attributes the cause of aggregate investment fluctuations to a collection of unspecified exogenous shocks outside of the model, because such a collection of shocks will form a Gaussian noise to the aggregate investment.

We propose an alternative model of endogenous investment fluctuations that has a robust nature to generate the exponential distribution. This econometrical model separates individual firms' interdependence reactions from the exogenous effects of common shocks. In financial economics, stock market volatility and the sources of such volatility have been extensively studied since the early 1960s. Measuring, modeling, and forecasting time-varying volatility are considered the central issues of asset pricing, portfolio management, and risk management (Fama (1965), Merton (1980), Engle and Gallo (2003)). Since the availability of high-frequency financial data, attention has been increasingly directed at the modeling of intraday volatility of asset prices and returns. A few studies have looked at the modeling

strategies of intraday volatility models (Engle and Chanda (2005), Andersen and Bollerslev (1997)). However, no empirical research of intraday volatility analysis has been applied at both a single stock level and industry level in the food industry.

The second essay of this dissertation empirically tests and estimates a modified High-Frequency Multiplicative Components GARCH model using a sample of interday and intraday trading data from over 30 publicly traded food sector companies in 2007. It also examines the dynamics between intraday return and overnight return. The persistence of intraday stock market return volatility leads us to the investigation of sources of market volatility. Stock market return volatility can be viewed as a reflection of market participants' reactions to market news. Food recall is a common practice in the food industry in the United States. From the discovery of the first case of Bovine Spongiform Encephalopathy (BSE), commonly known as Mad-Cow Disease (MCD), in the United States on December 23, 2003 to the E.coli O157:H7 outbreak that was associated with contaminated Dole brand baby spinach during the fall of 2006 to the most recent Salmonella outbreak traced to raw tomatoes, food safety and regulations have drawn more and more public attention. However, the effects of food recall announcements on the associated publicly traded firms in the food industry have not been adequately studied. The second essay fills this gap by examining the effects of the Food and Drug Administration (FDA) and U.S. Department of Agriculture (USDA) food recall announcements, which affected over 20 publicly traded companies in 2007. Results show strong evidence that the announcements of food recalls have negative impacts on the asset returns of the associated companies.

The rest of this dissertation is organized as follows: the first essay starts with a comprehensive review of the investment fluctuation and firms' interdependence behavior, followed by an econometric model of lumpy investments and an analysis of the binary choice behavior of firms' investments. The econometric model is empirically tested and estimated using a sample of Italian firm level investment panel data from 1983 to 1996. This econometrical model separates individual firms' interdependence behavior from the effects of common shocks. The last part of the first essay investigates the unique characteristics of the Italian

economy and discusses the economic policy implications of our research findings. The second essay is aimed at modeling and testing intraday volatility of asset prices and returns. It starts with a modified High-Frequency Multiplicative Components GARCH model, which breaks daily volatility into three parts: daily volatility, deterministic intraday volatility, and stochastic intraday volatility. Then we apply this econometric model to a single firm as well as to the whole food industry using the Trade and Quote and Center for Research in Security Prices data. This study finds that there is little connection between the intraday return and overnight return. There exists, however, strong evidence that the food recall announcements have negative impacts on the asset returns of associated publicly traded firms.

CHAPTER 2  
DISTRIBUTIONAL TEST FOR ENDOGENOUS EFFECTS:  
CASE OF BINARY INVESTMENTS

### 2.1 Introduction

Amplification mechanism of firms' investment demand has been a topic of extensive discussion. Amplification mechanism plays an important role in both natural and social science. For example, in electronic engineering, signal amplification has been used to explain the use of specific detection methodologies to directly increase the signal in proportion to the amount of target in the reaction. In medical science, gene amplification is referring to a cellular process characterized by the production of multiple copies of a particular gene or genes to amplify the phenotype that the gene confers on the cell. In biology, DNA amplification is a term to explain the production of multiple copies of a sequence of DNA or repeated copying of a piece of DNA. These different applications of amplification share a common feature, which includes a transmission or response system that delivers a signal from a certain type of origin to a single or multiple recipients. In economics, an amplification mechanism at the firm level directly leads to the comovement of firms' investment behavior, which is also known as aggregate investment fluctuation. The neoclassical model of investment shows that accumulation of capital reflects the slow adjustment of capital to its desired value. The transition path dynamics of capital adjustment implies that the speed of adjustment to the steady state is largely determined by the curvature of utility function (King and Rebelo (1988)). A synthesis of the neoclassical investment model with the assumption of convex adjustment costs provides conditions for inaction on investment due to the fixed costs of adjustment. In a seminal paper, Cooper, Haltiwanger, and Power (1999) assume a nonconvex cost of adjustment. Such an idea may seem sensible: in reality,



many investment projects are not possible in small quantities.<sup>1</sup> As a result, at the plant level we may expect to see periods of low investment activity followed by bursts of investment activity, which is formally documented as *investment spikes* or *lumpy investments*. Moreover, plant-level data show that lumpy investment is procyclical and more likely for older capital (Rothschild (1971) and Cooper, Haltiwanger, and Power (1999)). Our research is motivated by two key observations from investment activity studies: first, a significant portion of investment activity is associated with large variations in the capital stock at the plant level. Second, an increase in the frequency of investment spikes is a symptom of aggregate variations in investment. The second observation implies that investment activity at the extensive margin plays a major role in aggregate investment behavior.<sup>2</sup>

In investment fluctuation research, the questions that draw the most attention are the implication of a large investment episode and its linkage to the individual firm behavior. Cooper and Haltiwanger (1992) analyze a machine replacement model where individual plants decide upon the timing of machine replacement. Their research demonstrates that downturns are a good time for capital replacement since the opportunity costs are lower. In a variant of the machine replacement model, Cooper et al. (1999) focus on the threshold of investment spikes, which are defined as episodes of relatively large investment expenditures. The significance of their research is twofold. First, the machine replacement model allows them to analyze the relationship between the probability of a large investment episode and the timing elapsed since the last spike. Second, their research is among the pioneer work in explaining the empirical phenomena that, at plant level, bursts of investment are followed, on average, by periods of low investment.<sup>3</sup>

The focus of this paper is on the amplification mechanism behind the investment fluctuation. In particular, this paper stresses the importance of interaction effects of firms'

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<sup>1</sup>For instance, the construction of a new plant or the purchase of large machines requires large adjustments of capital stock. In this paper, we assume that small adjustments of the capital stock are either infeasible or undesirable. This assumption is also consistent with the *Menu Theory*.

<sup>2</sup>The effects of large investment spikes by a small number of firms are also confirmed by our data analysis, which shows that less than 2% of the total number of firms accounts for over 50% of the aggregate investment fluctuations. The correlation between the contribution of large investment episodes and the fraction of firms that experience large investment is 0.81. See Section 2.3 for more details.

<sup>3</sup>This is in contrast to the usual presumption of positive serial correlation in investment activity based on the standard convex adjustment cost model in the neoclassical analysis of investments.

investment behavior, which has been regarded as a possible source of comovements of investment demand at both firm level and sector level. In a classical paper, Long and Plosser (1983) show the sectoral production comovements due to the pecuniary externality among firms when they are linked by input and output relations. Models of information spillover explain the role of learning behavior of firms in the propagation of a firm's investment to others. In a more general context, models of interacting individuals have been studied and results suggest that the interaction gives rise to aggregate shifts in investment endogenously (Brock and Durlauf (2001) and Glaeser, Sacerdote, and Scheinkman (2003)). A common practice in empirical research is to use aggregate output as a demand-shift instrument for disaggregate industries. This can be interpreted as aggregate output that has a demand share for all industries while individual industries constitute only a small fraction of aggregate activity. However, aggregate output is not an adequate universal instrument for comovement attribution. By definition, aggregate output is a weighed average of all final goods across different sectors. Thus, the exogeneity and interdependence among different sectors raise the question of asymptotic bias. To address the issue of asymptotic bias, additional instruments are needed besides using the aggregate investment variable as an average measurement.

In a more recent paper, Shea (2002) focuses on the importance of input and output linkages, aggregate activity spillovers, and local activity spillovers to comovement in post-war U.S. manufacturing. Shea's research shows that complementarities contribute directly to aggregate volatility, even after the aggregate shocks are removed from the data. In particular, local spillover is the leading factor that explains between 15% and 36% of manufacturing employment volatility. Interindustry complementarity can be categorized into different forms, including input and output linkages (Long and Plosser (1983)), external economies of scale (Farmer and Guo (1994)), consumption complementarities (Verbrugge (1998)), trading externalities (Diamond (1982)), and aggregate demand spillovers (Murphy, Shleifer, and Vishny (1989)). In principle, interindustry comovement could be due entirely to effects of common shocks. For example, fiscal policy may directly affect the demand

for all capital goods. However, such comovement may also be driven by complementarities that propagate shocks across industries. For instance, the tax rebate policy may lead to comovement between the automobile industry and the steel industry not because of the direct effect of the tax policy on the steel industry but because the tax rebate generates a higher demand for automobiles and the demand shocks to the auto industry are spilled over to the steel industry. Complementarities do not simply imply the fact that the activity of Industry X will move together with that of Industry Y, it also suggests that the amount of comovement should be explained by the degree of linkage between X and Y.

The key question is how to separate the interaction effect from the common shock effects in the investment fluctuation. The common shock effects are also known as *exogenous effects*, while the interaction effects are documented as *endogenous effects*. However, it has been recognized that the models of endogenous effects are often unidentified econometrically. Manski (1993) formulated this as a reflection problem. Suppose that firm  $i$ 's investment  $x_i$  is positively affected by the aggregate investment in the reference group  $r$ , as  $x_{i,r} = \alpha + \beta \sum_{j \neq i} x_{j,r}$ .  $\sum_{j \neq i} x_{j,r}$  is the summation of all the firms' investments in reference group  $r$  except firm  $i$ . We can estimate  $\beta$  by a linear regression. However, a positive estimate of  $\beta$  does not necessarily imply the existence of the interaction effect, because a model with exogenous common shocks  $x_{i,r} = \alpha + v_r$  is observationally equivalent to the endogenous effect model.

The econometric unidentification problem is also discussed in a more general context of uncertainty on investment. Given the ambiguity of the relationship between uncertainty and investment, it is not surprising that little empirical work has been done aimed at sorting out various channels where uncertainty affects the investment and the business cycle theories (Caballero and Leahy (1996)). Theories of investment under uncertainty can be roughly classified into two groups. The first approach investigates firms in isolation and focuses on the factors affecting each individual's investment decision-making process independently. The second group looks at the firm in relation to other firms and emphasizes covariances in the investment activities and returns between investment projects. This paper takes an

approach similar to the second method that considers the interaction effect among firms' investment demand.

To isolate the effect of interindustry comovement from the effect of common shocks, most research has been focusing on the linkage between different industries. Shea (2002) introduces three models to examine the relationship between the observed comovements and measure of complementarity in the shortrun. The first model of factor demand linkages implies that the effect of a shock transmitted from Industry X to Industry Y depends on the strength of upstream and downstream linkages between X and Y. The second model of aggregate spillover suggests that the effect of a shock to X on Y depends on X's size.<sup>4</sup> The third model of local spillover implies that the effect of a shock to X on Y depends on both the size of X and the proximity between X and Y. Industries clustered in the same region are expected to generate strong comovement.

In this paper, we propose that a particular shape of the distribution of aggregate fluctuations may serve as a symptom that differentiates the endogenous effect model from the exogenous common shock model. Often the sources of the exogenous common shock are driven by many factors. In those cases, the central limit theorem predicts that the common shock should follow a normal distribution even when the factors that comprise the common shock follow non-normal distributions. Conversely, when we find a normal distribution in the aggregate variable, it is reasonable to include an unspecified set of exogenous common shocks in the model. When the aggregate fluctuations are driven by endogenous effects, to the contrary, the distribution of the aggregate may not necessarily follow a normal distribution. The distribution depends on the exact mechanism of the endogenous effects.

Even when the common shock has a particular distribution that is not a normal distribution, the normal distribution reappears for the aggregate actions if each action is independently affected by the common shock as in a binary model. Consider the following simple case of binary action models. There are  $N$  agents in each reference group  $r$ . Each agent can

---

<sup>4</sup>Shea's research results show a positive relationship between the size of industry and the degree of transmission. This research result is also confirmed by Baxter and King (1991). Baxter and King show that shocks to large industries have a larger aggregate impact than shocks to small industries, and, as a result, shocks to larger industries are transmitted to other sectors at a higher degree.

choose an action or inaction:  $a_{i,r} \in \{0, 1\}$ . Suppose that the probability for an agent  $i$  to act depends on a shock common to all the agents in the group  $r$ :  $\Pr(a_i = 1) = \alpha + v_r$ . Then, the distribution of the number of agents who act,  $\sum_{i=1}^N a_{i,r}$ , follows a binomial distribution. Hence, as  $N$  becomes large, the distribution of the normalized fraction of agents who act,  $\sum_{i=1}^N a_{i,r}/\sqrt{N}$ , asymptotically follows a normal distribution, regardless of the distribution of the common shock  $v_r$ .

The aggregate distribution does not necessarily follow the normal distribution if there are endogenous effects among the binary choice of firms, since the firms' actions are correlated in this case. Let us consider the simplest case of endogenous effects where the probability for agent  $i$  to act ( $a_{i,r} = 1$ ) depends on the realized action of its neighbor  $i - 1$ . Suppose that  $\Pr(a_{i,r} = 1) = \alpha + \beta a_{i-1,r}$ , where  $\alpha > 0$  and  $\alpha + \beta < 1$ . In this case, an action by  $i = 1$  may cause a domino effect to the successive agents. The distribution of the number of agents who act,  $\sum_{i=1}^N a_{i,r}$ , follows an exponential distribution.

The distribution shape depends on the precise structure of the interactions. In the case of the herd behavior model (Banerjee (1992)), for example, the agent  $i$ 's action is affected by the actions taken by all the agents who acted before  $i$ , i.e.,  $j = 1, 2, \dots, i - 1$ . We know that the distribution for the aggregate outcome in this case can degenerate to either all the agents act or no agents act. However, the exponential distribution appears to be robust as long as the domino effect does not degenerate to a deterministic cascade. We can actually show that the exponential distribution characterizes the aggregate outcome in the case of rational expectations equilibrium in which agents act simultaneously. Suppose that each agent has a random state variable,  $s_{i,r}$ , that is drawn from a uniform distribution over the unit interval. Suppose that agent  $i$  acts if  $s_{i,r} \leq \alpha + \beta \sum_{j \neq i} a_{j,r}/N$ . Thus, an individual firm's action depends on the realized aggregate actions of the reference group. An equilibrium action profile is determined for each realization of  $s_{i,r}$ . When  $N$  goes to infinity, there exists a unique equilibrium  $\sum_{i=1}^N a_{i,r}/N = \alpha/(1 - \beta)$ . When  $N$  is finite, a rational expectations equilibrium can deviate from the limiting equilibrium depending on the realization of  $s_{i,r}$ . We can show that the deviation of the aggregate outcome from the

limiting case follows a distribution that has an exponential tail.

Upon these observations, we utilize the empirical distribution of the aggregate outcome to test the endogenous effects model against the common shock model in a binary choice model of investments. Although several models have been proposed for the endogenous effects of firms' investments, there are few empirical investigations for the model, mainly due to the difficulty of the reflection problem. Recently, Guiso and Schivardi (2006) tackled the problem by utilizing additional information on the reference network among the firms as to who observes whom. In this paper, we analyze the same data set of Italian firms as Guiso and Schivardi but focus on the large investment episodes. We formulate the large investments as a firm's binary choice problem, and use the distributional information to investigate the endogenous effects for the large investments.

The rest of the paper is organized as follows. Section 2 presents a model of lumpy investment that generates the exponential distribution. The model provides the theoretical background that relates the distributional evidence and the estimation of the individual firm's behavior. Section 3 describes the data and presents empirical evidence that the fraction of firms that engage in large investments follows the exponential distribution rather than the normal distribution. We also employ a logit model to estimate the binary choice behavior of firms directly. The last part of Section 3 briefly discusses the economic development issue and some unique characteristics of the Italian economy. Section 4 concludes.

## 2.2 A Model of Endogenous Investment

### Fluctuations

Researchers have shown causality between individual firm's discreet investment and aggregate investment fluctuation at the industry or the national level. We provide a simple model to analyze the endogenous investment fluctuations of aggregate investments that arise from the interaction of the firm level lumpy investment behavior. The results show that the endogenous aggregate fluctuation may not follow a normal distribution even when the number of firms approaches infinity if the micro-level discrete investments exhibit strategic complementarity. This result contradicts with the traditional modeling strategy under the

assumption of central limit theorem. Specifically, we find that the distribution of aggregate fluctuation generates an exponential tail. This implies that the interaction of discrete investments at the firm level or the strategic complementarity overwhelms that law of large numbers effect in which idiosyncratic shocks cancel out each other.

Empirical studies on firm-level investment abound in recent years. Doms and Dunne's (1998) research demonstrate two distinct features of the capital adjustment at the establishment level: occasionally and significantly. Brock and Hommes (1997) introduce the concept of *adaptively rational equilibrium* (ARE), where agents adapt their beliefs over time by choosing from a finite set of different predictor functions conditioned on past observations. Their results lead to equilibrium dynamics of the endogenous variables. Other researchers develop interaction-driven models to investigate the aggregate fluctuations (Glaeser et al. (2003), Brock and Durlauf (2001), and Topa (2001)). Our model shows that the asymptotic distribution of the aggregate fluctuation demonstrates a heavier tail than the normal distribution even when the number of firms tends to infinity.

Consider that there are  $N$  firms that produce differentiated goods with a production function. This finding intrigues other macroeconomists to investigate the aggregate consequence of the micro-level lumpy investment adjustments (Cooper et al. (1999), Caballero and Engle (1999), Fisher and Hornstein (2000) and Khan and Thomas (2003)). Models of interactions and nonlinear dynamics are focusing on the possibility of endogenous fluctuations arising from the micro-level nonlinearity. The investment is a composite good produced by using all the  $N$  goods symmetrically by a CES (Constant elasticity of substitution) function. In summary, the production function is constructed as:

$$(2.1) \quad y_i = k_i^\alpha.$$

The investment process can be expressed as:

$$(2.2) \quad x_i = \left( \sum_{j=1}^N z_{i,j}^{1/\mu} \right)^\mu N^{1-\mu}$$

$$(2.3) \quad k_i = (1 - \delta)k_{i,0} + x_i.$$

The aggregate price index is normalized to one:  $P \equiv \left( \sum_{j=1}^N p_j^{1/(1-\mu)} / N \right)^{1-\mu} = 1$ . Then the derived demand for  $z_{i,j}$  is given in an isoelastic form:  $z_{i,j}^* = p_j^{-\mu/(\mu-1)} x_i / N$ . The minimum cost satisfies  $\sum_j p_j z_{i,j}^* = x_i$ .

There is a representative household who consumes a composite consumption good that is produced similarly as (2.2):  $C = \left( \sum_{i=1}^N z_{c,i}^{1/\mu} / N \right)^\mu$ . Then the derived demand for  $z_{c,i}$  has the similar form:  $z_{c,i}^* = p_i^{-\mu/(\mu-1)} C$ . The optimal average expenditure satisfies  $\sum_i p_i z_{c,i}^* / N = C$ .

The equilibrium conditions for the product markets are  $y_i = \sum_j z_{j,i} + z_{c,i}$ . Then, the total demand function is also isoelastic:  $y_i = p_i^{-\mu/(\mu-1)} (\sum_j x_j / N + C)$ . Defining the aggregate output as  $Y \equiv \left( \sum_{j=1}^N y_j^{1/\mu} / N \right)^\mu$ , we obtain  $\sum_j x_j / N + C = Y$  and the total demand function:

$$(2.4) \quad y_i^d = p_i^{-\mu/(\mu-1)} Y.$$

Each firm is a monopolistic supplier of a differentiated good. Suppose that it maximizes its profit  $\pi(k_i) = p_i y_i - x_i$  by choosing the capital level  $k_i$ , given the capital level in the previous period  $k_{i,0}$ . Assume that the firm can choose the capital level either at  $(1-\delta)k_{i,0}$  or  $\lambda(1-\delta)k_{i,0}$ , where  $\lambda > 1/(1-\delta)$ . This means that the firm can choose the investment rate  $x_i/k_{i,0}$  either at 0 or  $(\lambda-1)(1-\delta)$ . Namely, a firm can choose either a lumpy investment or an inaction.

By virtue of this assumption of the firm's binary investment, we can solve for an optimal inaction range of capital  $k_i$  in a simple manner. Let the lower bound of the inaction band be denoted by  $k^*$ . The upper bound is thus  $\lambda k^*$ . The optimal lower bound must satisfy an indifference condition  $\pi((1-\delta)k^*) = \pi(\lambda(1-\delta)k^*)$ . Now suppose that the initial capital  $\log k_{i,0}$  is an independent random variable that has a density function  $f$  over a finite support  $[\log k^*, \log \lambda + \log k^*]$ . Define  $\mu \equiv -\log(1-\delta) / \log \lambda$  and  $\phi \equiv f(k^*/(1-\delta))(\mu-1)/(\mu/\alpha-1)$ . Then the value of the bound is solved as:

$$(2.5) \quad k^* = a_0 K^{(\mu-1)/(\mu/\alpha-1)}.$$



where

$$(2.6) \quad a_0 = \left( \frac{\lambda^{\alpha/\mu} - 1}{\lambda - 1} \right)^{\mu/(\mu-\alpha)} (1 - \delta)^{-1}$$

$$(2.7) \quad K = \left( \sum_i k_i^{\alpha/\mu} / N \right)^{\mu/\alpha}.$$

The equilibrium condition is  $k_i \in [k^*, \lambda k^*]$  for all  $i$  where  $k^*$  is defined by (2.5). This condition allows multiple equilibria in general. Thus, we define an equilibrium selection algorithm by a best-response dynamics following Vives (1990) in order to choose a unique equilibrium. The equilibrium chosen by the best-response dynamics has a property that requires the minimum number of firms, among all the Nash equilibria, who adjust their capital other than the firms who adjust due to the direct effect of the depreciation.

The best-response dynamics is defined as follows. The initial state is:

$$(2.8) \quad k_{i,1} = \begin{cases} \lambda(1 - \delta)k_{i,0} & \text{if } (1 - \delta)k_{i,0} < k_0^* \\ (1 - \delta)k_{i,0} & \text{otherwise} \end{cases}$$

$$(2.9) \quad K_0 = \left( \sum_i k_{i,0}^{\alpha/\mu} / N \right)^{\mu/\alpha}$$

$$(2.10) \quad k_0^* = a_0 K_0^{\alpha(\mu-1)/(\mu-\alpha)}.$$

The subsequent dynamics are:

$$(2.11) \quad k_{i,u+1} = \begin{cases} \lambda k_{i,u} & \text{if } k_{i,u} < k_u^* \\ k_{i,u} / \lambda & \text{if } k_{i,u} \geq \lambda k_u^* \\ k_{i,u} & \text{otherwise} \end{cases}$$

$$(2.12) \quad K_u = \left( \sum_i k_{i,u}^{\alpha/\mu} \right)^{\mu/\alpha}$$

$$(2.13) \quad k_u^* = a_0 K_u^{\alpha(\mu-1)/(\mu-\alpha)}.$$

Define  $m_0$  as the number of firms that adjust upward in step  $u = 1$ . Define  $m_1$  as

$m_0 - \mu N$ . Define the number of firms that adjust upward in step  $u > 1$  as  $m_u$ . Define  $m_u$  as negative if the firms adjust downward. The number of adjusting firms are positive (negative) in every step if  $m_1 > 0$  ( $m_1 < 0$ ). Define  $T$  as the stopping time of the best response dynamics, i.e.,  $T = \arg \min_u m_u = 0$ .

Note that the initial aggregate capital  $K_0$  is defined at the level at which the depreciation is not taken into account. Thus,  $m_0$  is the number of firms that adjust upward due to the direct impact of the depreciation to each firm. If the investment of  $m_0$  firms meet the depreciation exactly, then  $m_1 = 0$  and, thus, the adjustment process stops. Define  $W$  as the equilibrium number of firms that engage in the lumpy investment after  $u = 2$ , namely,  $W \equiv \sum_{u=2}^T m_u$ . If there were a continuum of firms and if  $K = K_0$  at the equilibrium, then the fraction of firms that engage in the lumpy investment is  $\mu$ . In a finite economy,  $W$  indicates the deviation from the level that would be stationary in the continuum economy.

We state our main proposition here.

**Proposition 1** *When  $\lambda_i$  and  $\delta_i$  are heterogeneous across firms,  $W$  conditional to  $m_1$  obeys:*

$$(2.14) \quad \Pr(|W| = w | m_1) = C_0 (e^{\phi-1} / \phi)^{-w} w^{-1.5}$$

for a large integer  $w$ , where  $C_0$  is a constant.

Proof: See Nirei (2006a).

Proposition 1 shows that  $W$  follows a distribution that is a mixture of power and exponential. Since the exponential declines faster than the power, the tail of the distribution is dominated by the exponential part. This corresponds to our empirical finding that  $X$  follows an exponential distribution.

The parameter  $\phi$  is the mean number of firms that are affected when an additional firm engages in lumpy investment. Hence,  $\phi$  corresponds to the estimated slope in the logit regression  $d\Lambda/dX$ , which measures the increased probability of lumpy investment due to an increase in  $X$  (the fraction of firms that engage in lumpy investments in the same reference group). On the other hand, Proposition 1 shows that  $\phi$  characterizes the speed of

exponential decline in the tail distribution of  $W$ . Suppose that the exponential decline is fast enough that  $W$  is mostly characterized by the exponential part. Then, by Equation (2.14), the mean (and standard deviation) of the exponential is the inverse of  $\phi - 1 - \log \phi$ . Thus, Proposition 1 connects the two estimates in the next sections: the mean (and standard deviation) of the exponential distribution of  $X$  and the probability slope of the logit model  $d\Lambda/dX$ .

The mean of the exponential distribution of  $|Y|$  is estimated at 0.056. The average number of firms in  $G_{l,r}$  is 146 (by Table 2.1). Hence, the mean *number* of affected firms is estimated at  $146 * 0.056 \approx 8$ . By solving  $1/8 = \phi - 1 - \log \phi$ , we indirectly obtain the estimate of  $\phi$  as  $\hat{\phi} = 0.56$ . This does not exactly match the logit estimate for  $G_{l,r}$  that is,  $d\Lambda/dX = 0.33$ . However, it is interesting to observe that these measures fall in roughly the same ballpark even though they are derived from independent estimation.

The analytical result is sharpened when the lumpiness  $\lambda_i$  and depreciation  $\delta_i$  are homogeneous across firms.

**Proposition 2** *When  $\lambda_i$  and  $\delta_i$  are common across firms, then  $W$  follows a symmetric probability distribution function:*

$$(2.15) \quad \Pr(|W| = w \mid m_1) = m_1 e^{-\phi(w+m_1)} \phi^w (w+m_1)^{w-1} / w!$$

*The tail of the distribution function is approximated as:*

$$(2.16) \quad \Pr(|W| = w \mid m_1) \sim (m_1 e^{(1-\phi)m_1} / \sqrt{2\pi}) (e^{\phi-1} / \phi)^{-w} w^{-1.5}.$$

The proof of this proposition is presented as follows: We first derive the asymptotic distribution of  $m_1$ .  $m_0$  follows a binomial distribution with probability  $\mu$  and population  $N$ . Hence,  $m_1/\sqrt{N}$  asymptotically follows a normal distribution with mean zero and variance  $\mu(1 - \mu)$ .

Next we derive the asymptotic distribution of  $|\sum_{u=2}^T m_u|$  conditional to  $|m_1|$ . Without loss of generality, we consider the case  $m_1 > 0$ .

**Lemma 1**  $m_{u+1}$  conditional to  $m_u$  asymptotically follows a Poisson distribution with mean  $m_u \phi$  as  $N \rightarrow \infty$ .

Proof: See Nirei (2006b). First, we show that:

$$(2.17) \quad N(\log K_{u+1} - \log K_u) \rightarrow m_{u+1} \log \lambda.$$

Define  $\rho = \alpha/\mu$ . The Taylor series expansion of the left hand side yields:

$$(2.18) \quad \begin{aligned} N(\log K^{u+1} - \log K^u) &= \sum_{n=1}^{\infty} \sum_{j \in H_{u+1}} \left( \frac{k_j^u}{K^u} \right)^{\rho} \frac{\rho^{n-1} (\log \lambda)^n}{n!} + O(1/N) \\ &= \left( \frac{k^{*u}}{K^u} \right)^{\rho} \frac{\lambda^{\rho} - 1}{\rho} \sum_{j \in H_{u+1}} \lambda^{s_j^u \rho} + O(1/N) \\ &= \frac{\lambda^{\rho} - 1}{\rho} \frac{\sum_{j \in H_{u+1}} \lambda^{s_j^u \rho}}{\sum_{j=1}^N \lambda^{s_j^u \rho} / N} + O(1/N). \end{aligned}$$

The residual term in the first equation is of order  $1/N$ , because it consists of the terms involving  $\partial K^u / \partial k_j^u$ , which is of order  $1/N$ , and because the number of terms (the size of  $H_{u+1}$ ) is finite with probability one as is shown later. The second equation holds since  $k_j^{*u}$  is constant across  $j$ . For the same reason, the third equation obtains, since  $K^u = k^{*u} (\sum_{j=1}^N \lambda^{s_j^u \rho} / N)^{1/\rho}$  holds. The average  $\sum_{j=1}^N \lambda^{s_j^u \rho} / N$  converges to  $E[\lambda^{s_j^u \rho}]$  as  $N \rightarrow \infty$  almost surely. The expectation is equal to  $\int_0^1 \lambda^{s_j^u \rho} ds_j^u = (\lambda^{\rho} - 1) / (\rho \log \lambda)$ , because the following three facts hold as  $N \rightarrow \infty$  as we see later, namely,  $s_j^u$  for  $j \in H_1$  is uniformly distributed in  $[1 - 1/q, 1)$ ,  $s_j^u$  for  $j \notin \bigcup_{v=1}^u H_v$  is uniformly distributed in  $[0, 1 - 1/q)$ , and  $\bigcup_{v=1}^u H_v$  is finite with probability one. Also,  $\sum_{j \in H_{u+1}} \lambda^{s_j^u \rho}$  converges to  $m_{u+1}$  in distribution. This is because  $s_j^u < \phi(\log K^u - \log K^{u-1}) / \log \lambda$  for  $j \in H_{u+1}$  and the right-hand-side is of order  $1/N$  as (2.18) shows. Thus, the summation follows a binomial distribution. Hence, we obtain for

$u \geq 1$  a convergence in distribution:

$$(2.19) \quad N(\log K^{u+1} - \log K^u) \rightarrow m_{u+1} \log \lambda.$$

Next we examine  $m_u$  conditional to  $m_{u-1}$  for  $u \geq 2$ . We have  $\Pr(j \in H_u | j \notin \cup_{v=1,2,\dots,u-1} H_v) = (\phi(\log K^u - \log K^{u-1}) / \log \lambda) / ((N - \sum_{v=1}^{u-1} m_v) / N)$ . Thus,  $m_u$  follows  $\text{Bin}(N - \sum_{v=1}^{u-1} m_v, (\phi(\log K^u - \log K^{u-1}) / \log \lambda) / ((N - \sum_{v=1}^{u-1} m_v) / N))$ . This defines the stochastic process  $m_u$  completely. As we let  $N \rightarrow \infty$ , the limit (2.19) holds and the binomial distribution of  $m_u$  converges to a Poisson distribution with mean  $\phi m_{u-1}$  for  $u \geq 3$ . For  $u = 2$ ,  $m_2$  converges in distribution to a Poisson with mean  $\phi m$  where the distribution of  $m$  is defined conditionally on  $m_1$ .

Since a Poisson distribution is infinitely divisible, the Poisson variable with mean  $\phi m_{u-1}$  is equivalent to a  $m_{u-1}$ -times convolution of a Poisson variable with mean  $\phi$ .

Thus, the best-response dynamics is a valid algorithm of equilibrium selection (see Feller (1957)). Let  $T$  denote the stopping time. Using the previous asymptotic results, we have  $W \rightarrow \sum_{u=2}^T m_u$  in distribution. By using the property of the Poisson branching process (see Kingman (1993)), we obtain an infinitely divisible distribution called Borel-Tanner distribution for the accumulated sum  $W$  conditional to  $m_2$  as:

$$(2.20) \quad \Pr(W = w | m_2) = (m_2/w) e^{-\phi w} (\phi w)^{w-m_2} / (w - m_2)!$$

for  $w = m_2, m_2 + 1, \dots$ . By using  $m_2$  to follow the Poisson distribution with mean  $\phi m_1$ , we obtain (2.15) in the Proposition as follows:

$$\begin{aligned} \Pr(W = w | m_1) &= \sum_{m_2=0}^w ((m_2/w) e^{-\phi w} (\phi w)^{w-m_2} / (w - m_2)!) e^{-\phi m_1} (\phi m_1)^{m_2} / m_2! \\ &= (\phi m_1 e^{-\phi(w+m_1)} / w) \sum_{m_2=1}^w (\phi w)^{w-m_2} (\phi m_1)^{m_2-1} / ((w - m_2)!(m_2 - 1)!) \\ &= (\phi m_1 e^{-\phi(w+m_1)} / w) (\phi w + \phi m_1)^{w-1} / (w - 1)! \\ (2.21) \quad &= m_1 e^{-\phi(w+m_1)} \phi^w (w + m_1)^{w-1} / w! \end{aligned}$$

Approximation (2.16) is obtained by applying the Stirling formula  $w! \sim \sqrt{2\pi}e^{-w}w^{w+0.5}$ :

$$\begin{aligned}
& m_1 e^{-\phi(w+m_1)} \phi^w (w+m_1)^{w-1} / w! \\
& \sim m_1 e^{-\phi m_1} (e^{-\phi} \phi)^w (w+m_1)^{w-1} / (\sqrt{2\pi} e^{-w} w^{w+0.5}) \\
& = (m_1 e^{-\phi m_1} / \sqrt{2\pi}) (e^{1-\phi} \phi)^w w^{-1.5} (1+m_1/w)^w (1+m_1/w)^{-1} \\
(2.22) \quad & \sim (m_1 e^{(1-\phi)m_1} / \sqrt{2\pi}) (e^{\phi-1} / \phi)^{-w} w^{-1.5}.
\end{aligned}$$

This completes the proof.

Finally, we can show that the fluctuation of the *fraction* of investing firms,  $X = W/N$ , has a positive variance even at the limit of  $N \rightarrow \infty$  if  $\phi = 1$ .

**Proposition 3**  $\lim_{N \rightarrow \infty} \text{Var}(X) > 0$ , when  $\phi = 1$  and the distribution of  $s$  is uniform.

Proof: See Nirei (2006a)

## 2.3 Empirical Investigation

### 2.3.1 Data and Variables

We use longitudinal data of Italian firms drawn from the Company Accounts Data Service (CADS). We use its annual balance-sheet data on a sample of over 30,000 firms from 20 regions, 14 industries over a 14-year period from 1983 to 1996. The original data contains 306,364 observations and 47 variables. The main variables used in this paper include region code, industry code, profit, cash flow, investment rate, investment-over-capital rate, inflation rate, and real capital.<sup>5</sup>

We focus on the fraction of firms that experience large investment episodes in a given industry-region-year. First we define an investment-capital ratio,  $IPK(i, t)$ , for each firm  $i$  and year  $t$ . Then, we convert the investment-capital ratio into a binary variable,  $d(i, t)$ , which takes 1 if  $IPK(i, t) > \bar{d}$  and zero otherwise. We take the threshold  $\bar{d}$  at 20% for most

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<sup>5</sup>The original region and industry code data is a two-digit string variable. We do not have further information on the actual names of the represented region or industry.

TABLE 2.1

Descriptive Statistics for Variables in Logit Regression						
	Obs	Mean	Std. Dev.	Min	Max	Median
$d(i, t)$	281858	.233	.423	0	1	0
$X(G_l, t)$	3200	0.229	0.105	0	0.621	0.188
$I(G_l, t)$	2574	1.117	0.825	0.025	13.155	1.000
$N(G_l, t)$	3200	17898	13730	22	51739	1559
$X(G_r, t)$	3200	0.227	0.108	0.000	0.750	0.179
$I(G_r, t)$	2574	1.117	0.882	0.078	11.885	0.976
$N(G_r, t)$	3200	22478	26391	60	94008	432
$X(G_{l,r}, t)$	3200	0.227	0.137	0.000	0.866	0.191
$I(G_{l,r}, t)$	2574	1.221	1.371	0.000	15	0.901
$N(G_{l,r}, t)$	3200	1220	2194	10	16194	57

of our estimation.<sup>6</sup> Then we define the fraction,  $X(G, t) = \sum_{i \in G} d(i, t)/N(G)$ , where  $G$  is the reference group and  $N(G)$  is the number of firms in the group  $G$ . Since  $X$  is a fraction, its behavior can be overly volatile for the groups that have a small number of firms. We drop the groups that have firms less than 10.<sup>7</sup> We also define  $Y(G, t) \equiv X(G, t) - \sum_G X(G, t)/(\#G)$  in which the yearly effect on  $X(G, t)$  that is common across  $G$  is subtracted. Our main goal is to characterize the cross-section distribution of  $X$  (or  $Y$ ).

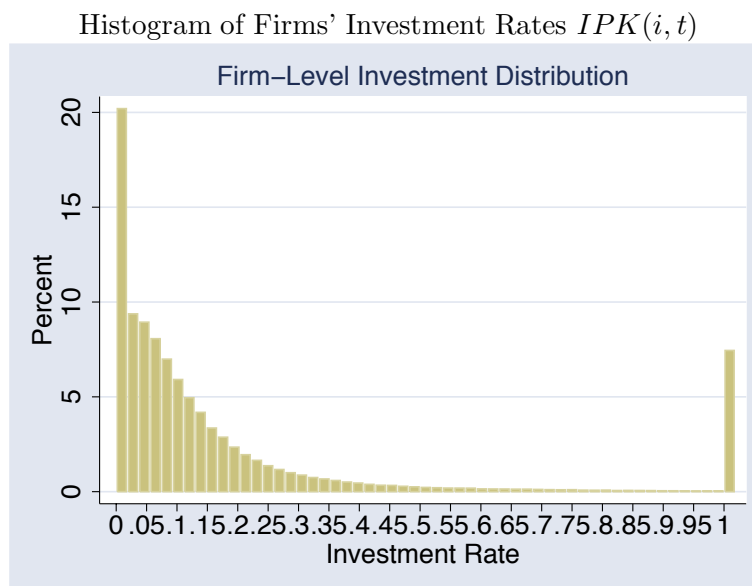
For most of the cases, we define  $G$  as a set of firms that operate in the same industry and region, denoted as  $G_{l,r}$ . For the regression analysis in Section 2.3.2, we also use the reference group where firms are in the same region but in different industries ( $G_r$ ). The regression analysis also uses an aggregate investment variable in order to capture its direct effect on  $d(i, t)$ . The aggregate investment is defined as  $I(G, t) = \sum_{i \in G} I_{i,t}/(\sum_{i \in G} \sum_t I_{i,t}/(N(G)T(G)))$ , where  $I_{i,t}$  represents the real investment of firm  $i$  in year  $t$ , and  $T$  is the total years in observation. The variables of interest are summarized in Table 2.1.<sup>8</sup>

<sup>6</sup>A similar pattern is found when we change the threshold to 30% and 10%. See Appendix Figure A.1 and Figure A.2.

<sup>7</sup>The original data file contains 306,363 observations. We exclude the year 1982 for nonvalid investment data and one outlier of the variable “ioverk.” This reduces the sample size to 291,933. Then we exclude small reference groups that contain less than 10 firms, which result in the sample size 281,858.

<sup>8</sup>Reference groups with less than 10 firms are dropped from the observation.  $G_l, t$  refers to the reference group in the same industry but different region in year  $t$ .  $G_r, t$  refers to the reference group in the same region but different industries in year  $t$ .  $G_{l,r}, t$  refers to the reference group in the same industry and same region in year  $t$ .

FIGURE 2.1



Our data analysis shows that the aggregate investment rate (investment-capital ratio), the portion of the aggregate investment rate that accrues to the large investments of individual firms, and that the fraction of firms that experience the large investments are positively correlated with each other: The correlation is 0.81 between the contribution of large investment episodes and the fraction of firms that experience large investment, 0.25 between the contribution of large investment episodes and the aggregate investment rate increases to 0.70 when the boom years 1994 to 1996 are excluded) and 0.19 between the fraction and the aggregate.<sup>9</sup>

Figure 2.1 depicts a histogram of  $IPK(i, t)$ . We can see that the distribution is highly skewed to the right. 24% of the samples have investment rates less than 2%. The tail is long, and it implies that a relatively small fraction of firms has a large impact on aggre-

<sup>9</sup>When we increase the threshold to 30%, the correlation between the contribution of large investment episodes, and the fraction of firms that experience large investment, correlation between the contribution of large investment episodes and the aggregate investment rate, and correlation between the fraction and the aggregate are 0.88, 0.27, and 0.14, respectively. When we drop the threshold to 10%, the correlation changed to 0.54, 0.61, and 0.32. As we expected, when we look at the more skewed tail part of the distribution, the correlations among the contribution, the fraction, and the aggregate become more evident.



gate investments.<sup>10</sup> The abnormally long tail of the investment capital ratio chart puts a question on the reason behind the engaging firm's investment behavior. We report two histograms of the investment spikes in the Appendix section<sup>11</sup>. The investment capital ratio is traditionally defined as capital accumulation over the initial capital level. The definition of capital accumulation is subject to controversy and ambiguity. Our research defines it as the real investment in tangible means of production. The measurement of accumulation is usually based on either the monetary value of investments or the change in the value of capital stock. Thus, in our paper a high rate of capital accumulation indicates a high level of investments in new construction or new tools. The German Economic Miracle in the 1930s to 1950s is one example of high investment capital ratio supporting growth. The cluster of high investment capital ratios among the Italian firms may be explained by the relatively small base of initial capital level since our research does find evidence that the majority of the Italian firms were small- and medium-size during 1980s and 1990s. Given a low base level of capital, any increase in the initial capital will produce a relatively high investment capital ratio. This investment spike can also be explained by governmental economic stimulus policies. For instance, it could be the case that a certain group of firms either in the same region or industry respond simultaneously to the favorable regional policy.

Figure 2.2 plots the histogram of  $X(G_{l,r}, t)$  for each year. The frequency on the vertical axis shows the number of firms at a particular level of investment. We observe a general pattern of the distributions: they are skewed to the right and their center location fluctuates over the years. Figure 2.3 shows the histogram of  $Y(G_{l,r}, t) \equiv X(G_{l,r}, t) - \sum_{l,r} X(G_{l,r}, t) / (\#G_{l,r})$ , in which the yearly effect on  $X$  is subtracted.<sup>12</sup> The histogram of  $Y$  is fairly symmetric.

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<sup>10</sup>A similar pattern is found when we change the threshold to 30% and 10%. See Appendix Tables A.1 and A.2.

<sup>11</sup>Figure A.3 shows the frequency of firms that experience investment rates from 1 to 50, and Figure A.4 depicts histogram of investment rates between 1 and 100.

<sup>12</sup> $\#G_{l,r}$  is the total number of years in reference group  $G$ .

FIGURE 2.2

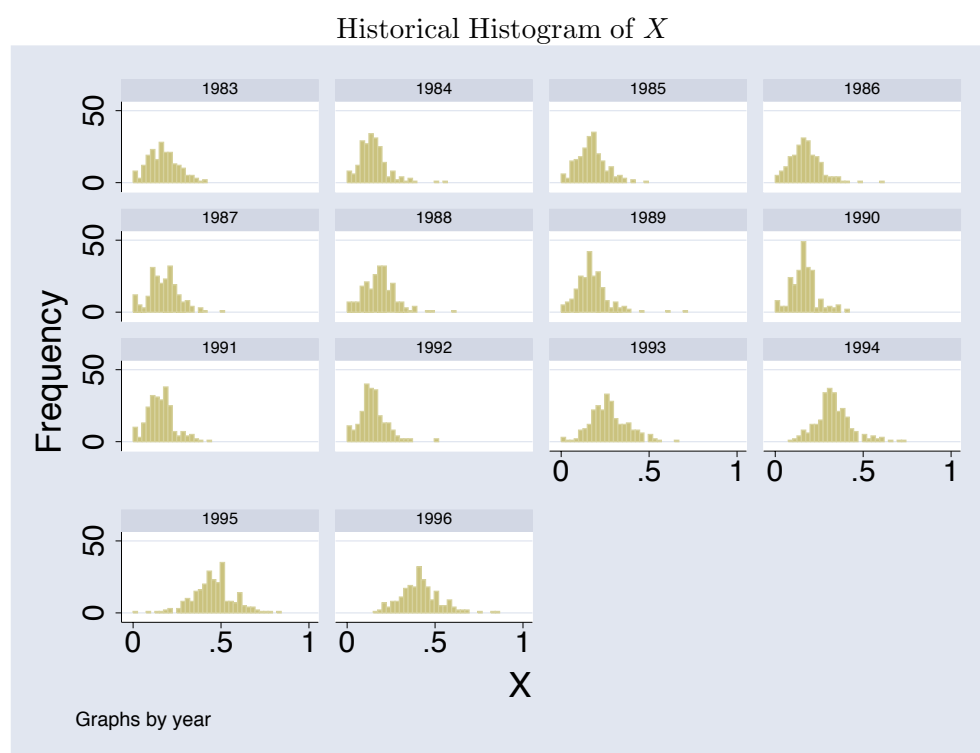


FIGURE 2.3

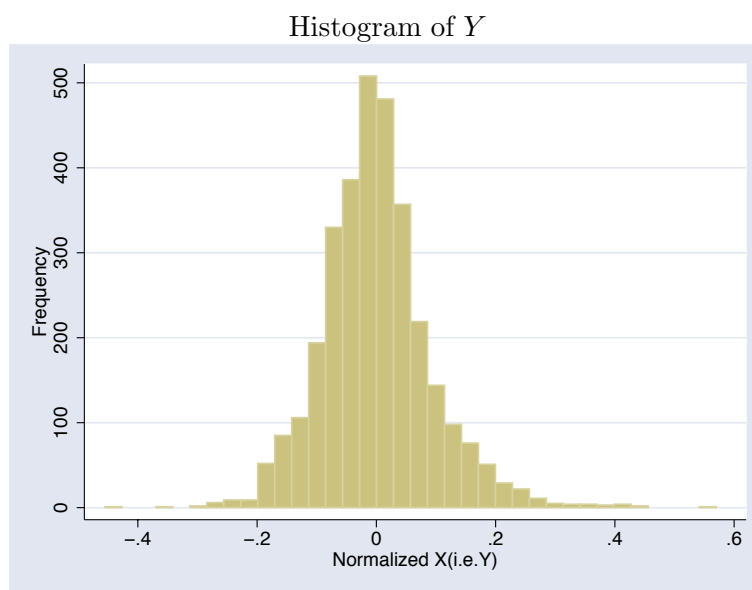


FIGURE 2.4

Semi-Log Plots of Cumulative Distribution of  $|Y|$  for Positive (Upper Line) and Negative Values (Lower Line).

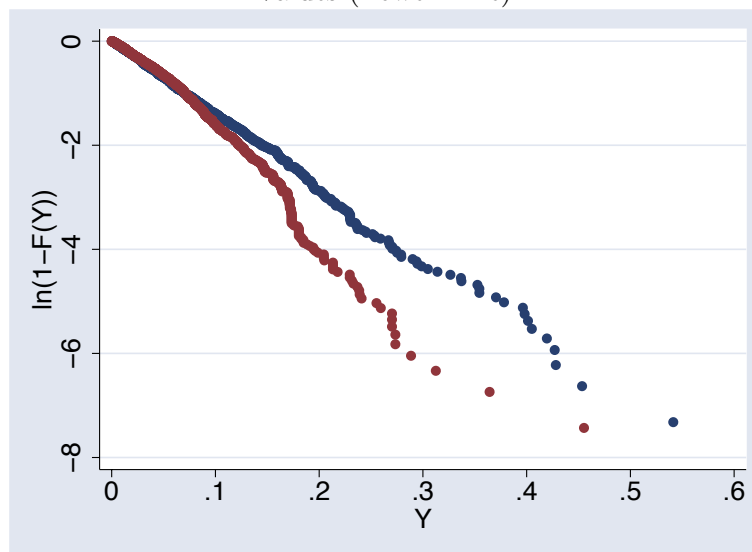


Figure 2.4 shows a semi-log plot of the same distribution of  $Y$ .

To produce the plot,  $Y$  is first ranked in a descending order, and the log of the rank divided by the total number of observations is plotted against  $|Y|$  for both positive and negative sides. In the semi-log scale, an exponential distribution function would show as a linear line. Our plot demonstrates that the positive side of the distribution of  $Y$  is well-represented by an exponential distribution. The negative side has a kink, beyond which the distribution shows a faster decline than the positive side. The faster decline in the negative side can be caused by the boundary effect on  $X$  which takes nonnegative values.  $X(G_{l,r}, t)$  has a mean of 0.23 and a standard deviation of 0.14 (from Table 2.1, hence, it is natural that the distribution of  $Y$  shows a boundary effect at around  $-0.15$ . This explanation is also consistent with the patterns of yearly distributions shown in Figure 2.2. The distribution is skewed in the years when the distributions are close to zero, such as in 1984 and 1992, whereas the distribution is not skewed in the boom years when the distributions are far from zero, such as in 1994, 1995, and 1996. The inverse of the slope of the semi-log plot provides an estimate for the mean (and also standard deviation) parameter for the exponential

TABLE 2.2

Skewness/Kurtosis Tests for Normality					
Variable	Observations	Mean	Std Deviation	Skewness	Kurtosis
Y	3,200	.000	.091	.592	5.194

distribution. A least-square regression for the positive side yields an estimate of the slope  $-14.128$  (standard error 0.017) with an R-squared 0.998, and the negative side yields an estimate of the slope  $-18.651$  (standard error 0.066) with an R-squared 0.980. As we can see from the semi-log plot, the positive side of  $|Y|$  is approximately linear, indicating that an exponential distribution fits the data fairly well.

The good fit by an exponential distribution also can be shown using a QQ-plot and empirical distribution test. Figure 2.5 plots the quantile of the exponential distribution against  $|Y|$  for negative value of  $Y$  (left) and the positive value of  $Y$  (right). For comparison purposes, we reported the quantile of the normal distribution against the total value of  $Y$  in Figure 2.6. The linear relation in the exponential QQ plots confirms our previous finding that the hypothetical distribution fits well to the empirical distribution, especially for the positive value of  $|Y|$ , which characterizes the investment spikes of the firms.

Now we examine statistical properties of hypothetical parametric distributions for  $Y$ . First we conduct the usual normality test based on higher moments. Table 2.2 shows the higher moments of  $Y$ . The large kurtosis indicates that  $Y$  is leptokurtic. The normality test, such as the Jarque-Bera statistic, overwhelmingly rejects the normality hypothesis.

Next we compare alternative parameterizations. We consider the case in which the distribution of  $Y$  follows exponential distributions for the positive side and the negative side follows with possibly a different mean, namely the likelihood function is  $\Pr(Y = y|y > 0) = \lambda_+ e^{-\lambda_+ y}$  and  $\Pr(Y = y|y < 0) = \lambda_- e^{-\lambda_- (-y)}$ . We call this an exponential distribution hypothesis. We also consider the case in which both positive and negative sides of  $Y$  follow an exponential distribution with the same mean  $1/\lambda$ :  $\Pr(Y = y) = (\lambda/2)e^{-\lambda|y|}$ .

Table 2.3 shows the results of the maximum-likelihood estimation for each distribution. The estimated mean of the exponential distribution is 0.071 (standard error 0.000) for the

FIGURE 2.5

QQ-Plots of  $|Y|$  Against the Exponential Distribution for the Positive (Right Column) and Negative Values (Left Column)

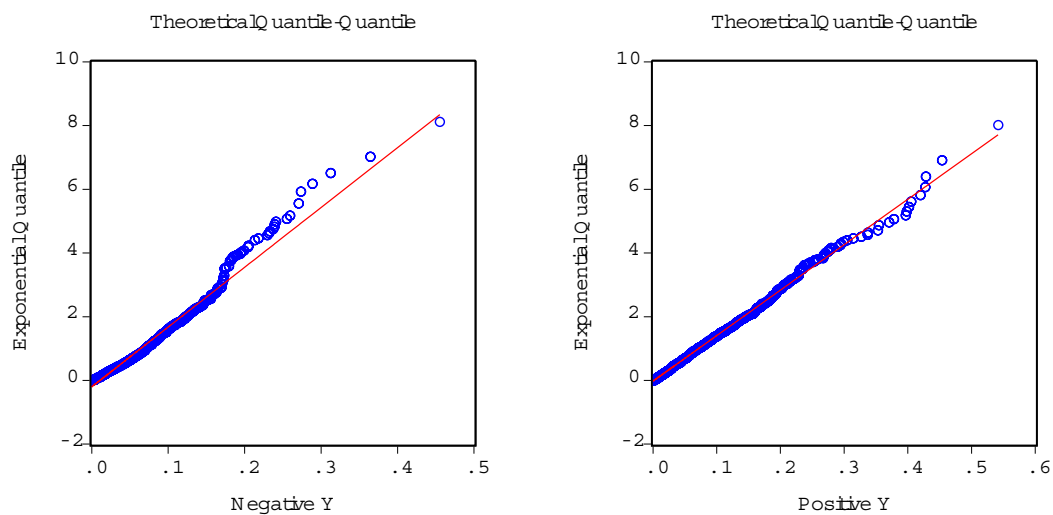


FIGURE 2.6

QQ-plot of Cumulative Distribution of  $|Y|$  Against Normal Distribution

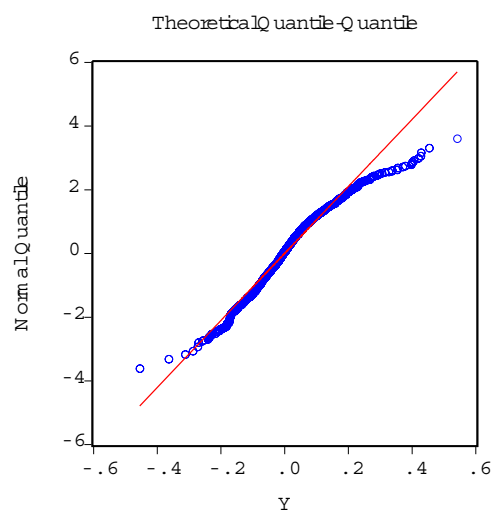


TABLE 2.3

Parameter Estimates for Each Distribution			
	Exponential	Laplace	Normal
Parameter 1	0.071 (0.002)	0.068 (0.001)	0.000 (0.002)
Parameter 2	0.064 (0.000)		0.076 (0.001)
Log-likelihood	3,204	3,200	2,990
Vuong's statistic	4.74		Null
		4.71	Null
	1.85	Null	

positive side and 0.064 (standard error 0.000) for the negative value of  $Y$ . The estimated  $\lambda$  for the Laplacian is 0.068, which is the middle value for the exponential slopes for the positive and negative sides. The exponential hypothesis has a larger log-likelihood value than the Laplacian hypothesis, because the Laplacian is equivalent to the exponential with restriction  $\lambda_+ = \lambda_-$ .

Note that the log-likelihood is the smallest for the Gaussian parametrization. We test the normality by utilizing Vuong's test based on Kullback-Leibler information criterion (Vuong (1989) and Greene (2000)). Let  $L(i; H)$  denote the likelihood of sample point  $i$  under the hypothesis  $H$ . Define the log-likelihood ratio for each  $i$  as  $m_i = \log L(i; H_1) - \log L(i; H_0)$ . Vuong suggested a statistic  $V \equiv \sqrt{N} \bar{m}_i / \text{Std}(m_i)$ , which follows a standard normal distribution if the hypotheses  $H_0$  and  $H_1$  are "equivalent" in the sense of Kullback-Leibler information. Thus, if  $V$  computed for  $H_1$  against the null  $H_0$  is greater than 1.96, then the null is rejected in favor of the alternative at the 5% significance level. Vuong's statistics are reported in the same table for the exponential and the Laplacian hypotheses against the Gaussian null hypothesis and for the exponential against Gaussian. The exponential and the Laplacian are favored more than the Gaussian at the 5% significance level, while the exponential against the Laplacian is inconclusive at 5%. In sum, our data on the distribution of the fraction of firms that engage in lumpy investments favor the model that generates an exponential distribution more than the models that generate normal distributions for the aggregate fluctuation of investments.

### 2.3.2 Logit Regression of Investment Choice

In this section we estimate the individual firm's decision on lumpy investment. Each firm faces a binary choice  $d(i, t) \in \{0, 1\}$  whether or not to engage in a lumpy investment. We formulate the binary choice by a Logit model whose independent variables include  $I_{-i,t}$  (the aggregate investment in the reference group  $G$  such that  $i \in G$ ),  $X_{-i,t}$  (the fraction of the firms that engage in lumpy investment in  $G \ni i$ ), and the firm's demographic characteristics. The variables  $I_{-i,t}$  and  $X_{-i,t}$  are defined slightly differently from  $I(G, t)$  and  $X(G, t)$  used in the previous sections. They do not include the contribution of the own investment of  $i$ , namely,  $I_{-i,t} = \sum_{j \in G, j \neq i} I_{j,t} / (\sum_{j \in G} \sum_t I_{j,t} / (N(G)T(G)))$  and  $X_{-i,t} = \sum_{j \in G, j \neq i} d(j, t) / (N(G) - 1)$ . It turns out that the lumpy investment is largely affected by  $X_{-i,t}$ , whereas the effect of  $I_{-i,t}$  is nonsignificant.

The comovement of investment problem is complicated by the common shock, which makes it hard to isolate the interaction among firms from the firm's reaction to the industrial shock to other industries in the same region. We address this problem starting with the identification of input and output linkages among different industries. This is inspired by Shea (2002). First we convert the original 4-digit industry code of the Italian firms to a 2-digit industry code that is consistent with the OECD classification.<sup>13</sup> With the data available, we end up with 25 industries. Secondly, we construct a dummy variable for the industry that is different from the region dummy and the year dummy. We use the 1985 version of the Italian transaction table to identify the industrial relation. The details of this dummy variable is discussed after the estimation. All the explanatory variables are constructed under the ISIC (International Standard Industrial Classification) classification.

In order to solve the endogeneity problem, we construct an instrumental variable to identify the portion of industry's investments that are induced by the exogenous industrial shocks. The direct logit regression of the binary lumpy investment dependent variable on  $X_{-i,t}$  and  $I_{-i,t}$  is not justifiable since the explanatory variable is composed of the left-hand-side dependent variable. So we use a two-stage least-squares (2SLS) method first proposed

<sup>13</sup>The second revision of the International Standard Industrial Classification (ISIC, Rev.2) is designed to ensure compatibility among all OECD countries. The detail of this conversion can be found at the OECD website: <http://www.oecd.org/dataoecd/48/43/2673344.pdf>.

by Vuong and Rivers.<sup>14</sup> In the first step we did an OLS regression of  $X_{-i,t}$  on the lagged  $I_{-i,t-1}$ <sup>15</sup> and industry dummy variable. In the second stage we use the estimated fraction variable as the instrumental variable (IV) in the logit regression.

*Stage 1.*-Obtain the least-squares estimator from regression of  $X_{-i,t}$  on the lagged  $I_{-i,t-1}$  and industry dummy:

$$(2.23) \quad \hat{X}_{-i,t} = \alpha_0 + \alpha_1 I_{-i,t-1} + \sum_{j=1}^{25} \alpha_j D_l,$$

where  $D_l$  is an industry dummy variable that equals to 1 for the industry-the same as in the dependent variable or in the closely related industry identified by the input-output linkage.<sup>16</sup>

*Stage 2.*-Estimate the probability of a firm experiencing an investment jump using logit regression.

Assume that the probability of a firm experiencing an investment jump follows a logistic distribution with parameter  $\beta Z_{i,t}$ :

$$(2.24) \quad \Pr(d(i, t) = 1) = \Lambda(\beta Z_{i,t}) = 1/(1 + e^{-\beta Z_{i,t}}),$$

where  $\beta Z_{i,t}$  is a linear combination of several independent variables:

$$(2.25) \quad \beta Z_{i,t} = \beta_0 + \beta_t D_t + \beta_l D_l + \beta_r D_r + \beta_x X_{-i,t} + \beta_I I_{-i,t} + \beta_c C F_{i,t} + \beta_{\Pi} \Pi_{i,t}.$$

Besides the fraction variable  $X_{-i,t}$  and the aggregate investment  $I_{-i,t}$  defined as before,

<sup>14</sup>See Chapter 15.5 of Greene (2000).

<sup>15</sup>In our regression we found that the OLS regression of  $X_{-i,t}$  on the lagged  $I_{-i,t-1}$  outperforms the OLS regression on  $I_{-i,t}$  of the same year. The estimated coefficient on lagged  $I_{-i,t-1}$  is around 0.004 at the 1% significance level.

<sup>16</sup>We use the Total (domestic+imported) Transactions Input Output Table of Italy in 1985, which is downloadable from the OECD website. First we formulate the industry share table, which shows the share of industry j's input demand for the total output of industry i. Then we pick a threshold value of the share to measure the strength of this industrial linkage. In other words, we label the linkage as strong if the share is above the threshold and weak if it is below. The share table is available upon request. The estimation results are not changed very much when we use the capital formation table.



$CF_{i,t}$  is the firm's cash flow,<sup>17</sup>  $\Pi_{i,t}$  is the profitability variables, and two dummy variables.  $D_t$  is a year dummy that equals to 1 for the year same as in the dependent variable, and  $D_r$  is a region dummy.

Tobin's q model and formula proposed by Hayashi (1982) were considered the standard measure of the unobservable productivity of capital. Firm's investment behavior is essentially driven by the marginal productivity of capital but without the data of the market values we build our model upon production data. Bayer (2006) proposed a gap model which measures capital profitability from the sales, employment and wage data. We follow the similar approach here. We start with the static optimization problem of a firm under a Cobb-Douglas production function:

$$(2.26) \quad Y = AL^{\alpha_L} K^{\alpha_K},$$

The variable A represents total factor productivity. The first-order conditions imply that:

$$(2.27) \quad wL = \alpha_L Y,$$

and

$$(2.28) \quad rK = \alpha_K Y.$$

When substituting optimal employment into the production function, we can get:

$$(2.29) \quad Y = [A(\frac{\alpha_L}{w})^{\alpha_L}]^{\frac{1}{1-\alpha_L}} K^{\frac{\alpha_K}{1-\alpha_L}}.$$

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<sup>17</sup>The importance of financing constraints suggests that cash flow plays an important role in a firm's investment spending. We include the cash flow variable here as a supplement explanatory variable to Tobin's q. The regression results are not affected very much when we exclude the cash flow variable.

After replacing back  $Y$  we can get a simple log form of measuring the profitability of capital,

$$(2.30) \quad \Pi = \ln(Y) - \frac{\alpha_K}{1 - \alpha_L} \ln(K).$$

The expenditure shares for both labor and capital are heterogeneous between firms and it is impossible to directly estimate  $\alpha_L$  and  $\alpha_K$  due to the dynamic structure of the panel data.<sup>18</sup> We calculated the expenditures share as the average level across all the firms by different industries.<sup>19</sup>

The parameter  $\beta_x$  measures the impact of the other firms' lumpy investments on the probability for  $i$  to choose a lumpy investment. The probability  $\Lambda$  increases to 1 when  $\beta_x$  increases to infinity, implying that the firm's investment is perfectly correlated with the other firms' lumpy investments at the limit  $\beta \rightarrow \infty$ ; When  $\beta \rightarrow 0$ , the probability becomes 0.5 regardless of the value of  $X_{-i,t}$ , implying that the firm is completely indifferent to the other firms' lumpy investments.

We choose the reference groups as industry-region-year and region-year. Since we are using industry input-output linkage, it makes more sense to investigate the inter-industry relation among the firms. We focus on the coefficients for  $X_{-i,t}$ . The estimation results are reported in Table 2.4. The estimated coefficient for  $X$  is about 5, and it is significantly different from zero at 1% for all specifications. The coefficient for  $\Pi$  is positive and significant while the estimate for  $CF$  is nonsignificant.<sup>20</sup> The marginal probability of the fraction variable  $X$  is .87 at the significant level. This shows that for a 1% increase of the fraction of the number of firms experiencing an investment spike, there will be a .87% increase of

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<sup>18</sup>See Bayer (2006) for more details on this exogeneity estimation issue.

<sup>19</sup>The total production  $Y$  is measured as sales. Labor cost is provided in our data and capital cost is calculated through the relationship that value added is the sum of labor cost, capital cost, and profits. The industrial expenditure share measure is preferred to the individual measure when we compare the regression results. This can be explained as a result of the heterogeneity across firms.

<sup>20</sup>In the literature it has been documented that additional cash flow variable becomes insignificant when it is used as an alternative measure of Tobin's  $Q$ . But it is slightly different since we use it along with the Tobin's  $Q$ . Actually, when we drop the profitability variable, the estimate on cash flow is still insignificant. For more discussion see Cummins, Hassett, and Oliner (1999) and Vlieghe, Bond, Klemm, Newton-Smith, and Syed (2003).

TABLE 2.4

Estimation Results of the Logit Model

	Industry-Region-Year	Region-Year
Constant	-1.162 (.324)	-3.247 (1.077)
$X$	5.825 (.333)	12.703 (4.482)
$I$	-.019 (.010)	-.004 (.015)
$\Pi$	.004 (.001)	.006 (.001)
$CF$	.000 (.000)	-.000 (.000)
$\partial\Lambda/\partial X$	.870 (.060)	1.915 (.676)
$\partial\Lambda/\partial I$	-.001 (.001)	-.001 (.002)
$\partial\Lambda/\partial \Pi$	.001 (.000)	.001 (.000)
$\partial\Lambda/\partial CF$	.000 (.000)	.000 (.000)
Log-Likelihood	-61513.000	-60565.000

the probability of a single firm increasing its own investment level.

### 2.3.3 Italian Economy Investigation and

#### Economic Development Implications

Our study shows that some unique characteristics of the Italian economy provide us with an ideal platform for the empirical research on individual firm investment behavior analysis during the 1980s and 1990s.

The main characteristic of the Italian economy in the postwar period includes a series of profound dualisms: the industrialized North and the underdeveloped South, the public and private sectors, and large industrial corporations and small family-type businesses. Efforts of the state to mitigate gaps among regional imbalanced development resulted in public sector inefficiencies and redundant industrial projects. The economic policy of Christian Democrats, which dominated Italian politics for a long time, was expansionary and un-

stable.<sup>21</sup> The solution to the troubled economic system lies in small- and medium-size enterprises, which is considered as the backbone of the Italian economy.

The logit regression results indicate a significant level of clustering of investment fluctuation. Table 2.4 shows that firms are not responsive to the aggregate level of investments but reactive to other firm's behavior within the same reference group. Also the level of interaction among the firms varies according to different reference groups. Our research finds that when there is a 1% increase in the fraction of firms engaging in lumpy investments, the *probability* of an individual firm in the same region and same industry increasing its investment will increase by .87%. If the firm is in the same region but from different industries, the probability jumps to almost 2%. This result serves as an indication that the clustering of firms' investments may also be affected by factors outside of our model. Based on our investigation of the Italian economy, there is one distinct characteristic that gives us more insight into this interdependence behavior of firms' investments-the industrial district. These industrial districts are geographically defined production systems characterized by a large number of firms that are involved at various stages and in various ways in the production of a homogeneous product (Pyke, Becattini, and Sengenberger (1998)). Most of the small- and medium-size firms are concentrated in traditional sectors such as textile, footwear, leather products, ceramic tiles, wooden furniture, musical instruments, and machine tools. The majority of successful small firms have been clustered in industrial districts since at least the 1970s.<sup>22</sup> By 1981, more than three-quarters of Italian manufacturing was in firms with fewer than 500 employees. In 1992, small- and medium-size firms captured 70% of total sales in the Italian economy and 40% of the country's exports (Sharpe (1992)). In particular, the geographic concentration of small firms in manufacturing sectors is gen-

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<sup>21</sup>Management positions in public sector companies became the main source of patronage, and state-owned enterprises became instruments of industrial policy. The inefficient industrial policy consisted of random public interventions, including extensive bailing out of large failing private companies. Such intrusion of the state politics in the economy also created numerous opportunities for corruption. See Baldassarri and Modigliani (1998) and OECD Economic Survey: Italy 1990/1991 (OECD (2002)).

<sup>22</sup>For example, in northeastern Italy, there is a triangle business district geographically defined by Udine, Pisa, and Ascoli Piceno, and centered in Bologna and Florence. The majority of successful small firms have been clustered in industrial districts. For example, textiles are principally manufactured in Prato and Biella, furniture in Poggibonsi, ceramic tiles in Sassuolo, kitchen utensils in Omegna, and sport files in Gardone Val Trompia.

erally considered as the essential feature of the Italian industrial districts. There are two crucial characteristics of the industrial district: first is the existence of networks between small firms; and a second feature is the combination of cooperation and competition among the firms. The flexibility of labor is particularly important to the economies of scales for the district as a whole. The international competition pressure resulted in a delicate balance between the readiness to share information and services and competition on a wide range of scales, such as price, quality, design, and speed (OECD (2002)).

The interaction among small and medium-sized firms in industrial districts during the 1980s is the essence of the Italian economy's competitive advantage in the traditional industrial sector. The possible drawbacks of small volume production are offset by the effects of economies of scale. These economies of scale effects are external to the firm but internal to the district (Pyke et al. (1989)). The geographical concentration and size advantage directly contribute to the firms' flexibility and ability to generate external economies. The flexibility consisted of speed of adjustment and innovation.<sup>23</sup> This has enabled firms to continuously innovate and upgrade production line and capture the market share at the most profitable level. The cooperation and competition among the firms in the industrial districts also generate other externalities to the economy as a whole. These externalities include knowledge and skills training, research and development funding, information sharing and communication among the market. It is the balance between cooperation and competition that enable industrial districts to achieve the efficiency of vertically integrated corporations without losing any of their flexibility (OECD (2002)). Sociologist Carlo Triglia has summarized the sources of success of small- and medium-sized firms into three factors: first, interaction of small- and medium-size urban centers with traditional goods production skills directly cultivated entrepreneurship and innovation; second, family-based agricultural structure that ultimately supplied inexpensive source of labor to the industries; and third, Catholic and socialist political traditions with a focus on the creation of a middle class social base.

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<sup>23</sup>Evidence of firms' quick response to market signals and change of the business environment can be found in OECD Economics Survey: Italy 1988/1989 (OECD (2002)).

TABLE 2.5

Selected Variables in Public Sector Finance (Percentage Ratios to GDP)

	1979	1986	1991
Total spending	41.2	51.53	9.0
Interest payments	5.8	5.10	2.0
Personnel	10.8	11.7	12.7
Pensions	9.6	11.2	12.4
Transfer to enterprises	2.8	3.1	2.4
Total revenues	31.6	39.4	43.7
Tax revenues	16.5	21.9	25.6
Social security contributions	12.8	13.9	14.7
Total debt	61.6	88.2	104.0

Our research finds that there is another important factor that is unique to the Italian economy—the nation’s inefficient political system and government policies. Paradoxically, the state often intervened to protect big industries and large enterprises for geopolitical reasons, which decreases the efficiency of the whole economy, but, at the same time, it resigned the regulation responsibility of small industries almost entirely to the private sector. Evidence of the government’s loss of regulation can be found in tax evasion, unregulated labor, and communal welfare during the economic hardship. For instance, the exemption of firms with fewer than 15 employees from job protection legislation until May 1990 resulted in a surge in the small firm employment during that period. The freedom in the small industries, especially in the labor section, contributed significantly to the growth of the Italian economy during the 1980s. Table 2.5 reports selected variables in the public sector of finance of the Italian government during the 1980s and 1990s (Miscossi and Padoan (1995)).

However, the combination of economic and political crisis, coupled with Italy’s entry into the European Monetary System (EMS) and the signing of the Maastricht Treaty, put the Italian economy into a serious postwar crisis and the nation’s worst recession in 1992.<sup>24</sup> Both EMS and the Maastricht Treaty severely limited the state’s power in economic matters. The recession in 1992 was considered the realization of the failure of the Italian

<sup>24</sup>In September 1992, the government of Giuliano Amato was forced to abandon the EMS and devalue the currency.

economic model, which is constructed around mass political parties, large public sector, and state protection of the largest industries. This model relied on excessive deficit spending, including both public deficit and current account deficit, which required high interest rates to ensure a continued placement of the public debts and maintenance of the lira exchange rate. The high interest rates squeezed out private investments and boosted import industries. Small- and medium-sized firms were suffering from the economic crisis as well. The new challenges and difficulties demanded a revolutionary change in the Italian economic model, especially a reduction in costs imposed by the inefficient infrastructure of services and public administration. In general, flexibility and efficiency at the firm level were no longer sufficient to save the economy and restructuring was needed in the state and local public sector (Lane (1992)).

Based on the model analysis and the investigation of the Italian economy in the 1980s and the 1990s, our research shows that firms are reactive to the total number of firms that exhibit large investment behaviors while irresponsible to the aggregate level of investment in the same reference group, i.e., industrial districts. We can also extend this argument to the framework of economic development.<sup>25</sup>

Among the different theories of economic development, the most popular theories are economic base theory, sector theory, and growth pole theory.

The first two theories are based on certain classifications of the economy's industries. Economic base theory categorizes the economy into basic and nonbasic sectors. Sector theory categorizes the economy into primary (agricultural, forestry, and fishing), secondary (manufacturing and mining), and tertiary (trade and services) sectors. The essential dynamics of development are based on the external demand for a region's products and the economic base multiplier effects. According to these two theories and their application to our investment interaction analysis, government should focus on industrial recruitment and promotion in the basic sector or primary sector and facilitate expansion of existing export

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<sup>25</sup>The Economic Development Administration summarizes the importance of understanding the economic development theory in the following terms: "Theories used by economic developers determine, either explicitly or implicitly, how these developers understand economic development, the questions they ask about the process, the information they collect to analyze development, and the development strategies they pursue" (EDA (2007), p.2).

industries through infrastructure upgrades. The major weakness of economic base theory is its arbitrary distinction between basic and nonbasic sectors, and failure to recognize that regional economies are an integrated component of mutually dependent activities. Similarly, sector theory focuses on the internal economic structure and the local economy but fails to account for the role of exports in local growth. The government can improve the overall efficiency of the economy through reconciliation between the basic and nonbasic sectors and by promoting the effects of economies of scale.

Growth pole theory is also known as theories of concentration and diffusion, which focuses on industries that attract growth and leads to backwash effects for surrounding areas. The crucial question is the identification of those growth poles or growth centers. Based on our previous analysis, government policy will be more efficient if it targets at stimulating more firms in investment behavior rather than increasing the overall level of investment. There are a number of ways governments at both national and local levels can promote the development of the overall economy. The most direct method is through public investment in infrastructure, such as transportation, communication, power, hi-tech or research center, and education system. The second channel is through the public subsidy of private investment, including tax abatement, purchase of property, incentives to relocate, etc. The policy implication of our research for the local government is to allocate the budget in such a way that would benefit a wide range of firms rather than benefiting a concentrated number of firms or a particular region.

## 2.4 Concluding Comments

This paper argues that the distribution of the fraction of firms that engage in large investments provides a useful test for the existence of endogenous effects among the firms' investment decisions. Testing of the endogenous effects is often a challenge because it is observationally equivalent to the model with exogenous common shocks. We argue that, in a binary choice model, the common shock results in the normal distribution of the number of firms that engage in the lumpy investment whereas the endogenous effects leads to a nonnormal distribution that is better characterized by an exponential distribution.



We investigate the panel of investment data for Italian firms. We construct the fraction of firms that engage in the investment with which the investment-capital ratio of the firm exceeds a certain threshold. The fraction samples are constructed for three definitions of reference groups, namely, a region-year cell, an industry-year cell, and a region-industry-year cell. Those samples constitute a distribution of the fraction of investing firms for each definition of the reference group. The results show that the normal distribution hypothesis is rejected by the empirical distributions, whereas the exponential distribution hypothesis is consistent with the empirical distributions.

We present a simple model of lumpy investments when there are strategic complementarity among the firms' investment decisions. The complementarity stems from the fact that firms are linked by input and output relations. When a firm has more capital, the price of the product of the firm is reduced, which gives an incentive to produce more for the firms that use the product as an input. This model generates a nonnormal distribution with exponential tail for the fraction of firms that invest in a rational expectations equilibrium.

We take a further step to investigate the empirical evidence of the interdependence behavior of firms' investment in the Italian economy. Our empirical investigation results can be summarized as: first, interaction of small- and medium-size urban centers with traditional goods production skills directly cultivated entrepreneurship and innovation; second, family-based agricultural structure that ultimately supplied inexpensive source of labor to the industries; and third, Catholic and socialist political traditions with a focus on the creation of a middle class social base.

The model implies that the degree of strategic complementarity across the firms determines the mean and standard deviation of the exponential distribution for the aggregates. We investigate this relation by directly estimating the firm's binary behavior with the same data. The result is consistent with the model predictions.

CHAPTER 3  
DECOMPOSITION OF DAILY VOLATILITY:  
INTRADAY VOLATILITY AND OVERNIGHT SURPRISES

### 3.1 Introduction

#### 3.1.1 Measurement of Daily Return and Volatility

It is a tradition to measure the stock market returns as the log-difference of the closing prices. Amihud and Mendelson (1987) and Stoll and Whaley (1990) compare the returns using closing prices with returns using opening prices. Stoll and Whaley show that the ratio of variance of open-to-open returns to close-to-close returns is consistently greater than one for New York Stock Exchange (NYSE) common stocks during the period 1982 through 1986. They give a number of reasons for the increase in the volatility of open-to-open returns, such as private information revealed in trading, temporary price deviations induced by specialists and other traders, and specific trading mechanism at work. Dow and Gorton (1993) show that different trading mechanisms, such as limit order market, dealer market, and bargaining and crossing networks market have different impacts on both variances of open-to-open and close-to-close returns. The news and information flow also play an important role in explaining asset price volatility. The announcement made when the market is closed will definitely affect the opening price of the next day's market. In this paper we assume that all the information accumulated overnight is reflected in the first opening price exclusively.

Besides the traditional measurement of daily returns volatility as the variance of log-difference of closing prices, there are two other popular concepts related to volatility:<sup>1</sup> high-

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<sup>1</sup>See Taylor (1987), Ding, Granger, and Engle (1993), and Granger and Sin (2000).

low spread and realized volatility. The high-low spread refers to the price difference between the highest and the lowest recorded daily price, and it is a function of the volatility during the day. Considerable modeling strategies are devoted to improving the daily volatility forecasting using the high-low spread (Taylor (1987), Chou (1988), and Alizadeh, Brandt, and Diebold (2002)). Realized volatility is proven to be a consistent estimator of the quadratic variation of the underlying diffusion process under certain assumptions. One distinct feature of realized volatility is its use of the regular intraday interval sampling, which has been proven to be an effective tool in analyzing intraday volatility. The main differences between these three variables, namely the variance of log-price difference, high-low spread, and realized volatility, can be summarized as follows: the variance of log-price difference of daily return utilizes closing prices of the previous day, while the high-low spread includes all trade information during the day, and the realized volatility focuses on quotes sampled at discrete intervals during the day.<sup>2</sup>

This paper uses the log-difference of the closing prices as the measurement of daily return. We can present the daily return as:

$$(3.1) \quad r_t = \log(C_t) - \log(C_{t-1})$$

$$(3.2) \quad = \log(C_t) - \log(O_t) + \log(O_t) - \log(C_{t-1})$$

$$(3.3) \quad = c_t - o_t + o_t - c_{t-1}$$

$$(3.4) \quad = r_t^I + r_t^O$$

where  $C_t$  refers to the closing price at time  $t$ , and  $O_t$  refers to the opening price at time  $t$ . The lower case letters  $c_t$  and  $o_t$  denote the logarithms of the closing and opening prices, respectively. By adding and subtracting the log of opening prices, we divide the daily returns into two parts: the intraday return, and overnight return. In this way the daily return is decomposed into two parts: intraday return, denoted by  $r_t^I$ , and overnight surprises, denoted by  $r_t^O$ .  $r_t^I$  is defined as the log-difference of the closing price and opening

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<sup>2</sup>Engle and Gallo (2003) give a more detailed discussion on the comparison among these three measurements of daily and intraday volatility.

price, while  $r_t^O$  represents the log-difference of the price of the previous day's closing and today's opening price. This decomposition is first introduced by Engle, Ito, and Lin (1990) in the research of spillover effects on volatility of stock indices between Tokyo and NYSE.

The previous studies on intraday volatility have primarily focused on modeling selection from an econometric standpoint. Among these prior efforts, however, the majority were devoted to improving the modeling of the intraday return volatility within the aggregate capital market, and, thus, their conclusion may not be applicable to a certain industry or a single stock analysis. In addition, very little research of the same nature has been conducted on the joint analysis of intraday and overnight returns.

This paper starts with analyzing the modeling strategy of intraday volatility. We adopt a modified GARCH model for high-frequency intraday financial returns originally developed by Engle and Chanda (2005). By using the High-Frequency Multiplicative Components GARCH model, we are able to isolate the intraday volatility from interday volatility. Engle's original model has two distinct features that are different from other intraday volatility models. First, the intraday components contain both a deterministic and a stochastic part. Second, the multiplicative specification of the variance structure generates better statistical implications. Estimators from the multi-step estimation are consistent and asymptotically normally distributed. In Engle's paper, he defines bin as the 10-minute interval during the day and he excludes the overnight return, which is represented by bin zero in the model. Our model is different from Engle's model in two major ways: the first contribution is the extension of Engle's model to recover the overnight returns. We believe that the price change between the previous day's closing price and today's opening price conveys important information in volatility analysis. We apply the model to a single stock and the entire industry.<sup>3</sup> The second contribution is the specification of the intraday price change. By including all tick-by-tick trade quotes, our model captures more market price change information compared to the fixed interval categorization.

Section 3 of this paper focuses on the dynamics between intraday and overnight returns using the sample of top ten most actively traded stocks in three food sectors: the food

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<sup>3</sup>We include the top 20 companies in each industry categorized by market capitalization.

retailers and wholesalers sector, the restaurant and bars sector, the food products sector from January 1 to December 31, 2007. Our research results have three main findings: First, overnight return has marginal impact on intraday return. Second, intraday return has no explanatory power in analyzing the overnight return. Third, the overnight return of the food products sector in general is more sensitive to the intraday return than the food retails and wholesales sector and the restaurant and bars sector based on our sample. We also study the effects of food recall on the dynamics between intraday and overnight returns for two specific cases involving two companies in the food products sector.

Since we choose a specific type of news shock to the food industry, we perform an event study on the food recall in Section 3.4 of this paper. Our purpose is to assess the economic impact of recalls on the company's asset returns in the stock market. Using a data set of food recall announcements during 2007, this study investigates whether there is evidence of asset return losses associated with recall announcements. The findings of the event analysis confirm the negative impact of recall announcements on the associated firms' stock market returns. Our study also suggests possible insider-trading activities by examining the behavior of abnormal returns changes around the recall announcement date.

### 3.1.2 Models of Volatility Forecast

Since Engle's (1982) seminal paper on ARCH (Autoregressive Conditional Heteroscedasticity) model, financial econometrics literature has been focusing on measuring, modeling, and forecasting time-varying volatility, which are considered the central issues to asset pricing, portfolio allocation, and risk management. Andersen, Bollerslev, and Diebold (2008) define three different volatility concepts: the notional volatility corresponding to the *ex post* sample path return variability over a fixed time interval, the *ex ante* expected volatility over a fixed time interval, and the instantaneous volatility corresponding to the strength of the volatility process at a given point in time. Measurement of return volatility requires decomposition of a given price movement that represents a return innovation as opposed to an expected price change. The initial developments are largely parametric, but the recent literature has moved towards nonparametric approaches. Based on these three different re-

turn volatility concepts by Andersen, Bollerslev, and Diebold (2008), parametric modeling strategies assume that the expected or instantaneous volatility follow a certain functional format for both discrete and continuous time stochastic volatility models. So the essential difference between parametric and nonparametric methods is that the parametric approach is based on explicit functional form assumptions, while the nonparametric approach is generally free from such functional form restrictions. Nonparametric approaches are able to estimate notional volatility that is flexible but consistent when the sampling frequency of the underlying asset returns increases.

Volatility forecasts are commonly used in a variety of financial market activities. In risk management, a risk manager will want to know the probability that the investment value will either appreciate or decline in the future. In derivative pricing and trading, an option trader is most interested in the volatility involved in the contract today and the potential change of this volatility in the future life of the contract. In portfolio selection, a portfolio manager needs to adjust the market positions according to the change of the volatility of underlying assets in order to meet the preset investment goals. In a market-making case, a market maker may want to build a larger bid-ask spread to catch the profits if he believes the market will be more volatile in the future. In general, the study of volatility is valuable to any market participant whether he wants to hedge the risk of volatility or to profit from the increased volatility.

However, research on financial time series has long been challenged by the unpredictable feature of future asset prices and returns. Such unpredictability drives research on the assumption of the linearity of the asset prices time series. Campbell, Lo, and MacKinlay (1997) make the distinction between *linear time series* and *nonlinear time series*. In linear time series, shocks are assumed to be uncorrelated but not necessarily identically independently distributed. In nonlinear time series, shocks are assumed to be identically independently distributed, but there is a nonlinear function relating the observed time series and the underlying shocks. However, given the full information on the historic values of the series, or even the most current available market information, it is still hard to know what

will happen tomorrow. In econometrics terms this is documented as a martingale difference process. The term martingale difference process stems from the fact that a process can always be generated as a difference of a martingale process and in this sense, a martingale difference process can be thought of as a building block process for a martingale. The crucial statistical property of a martingale difference process is that the conditional mean with respect to its past is zero. This turns out to be an important assumption in our intraday volatility model. In recent years there has been a tremendous research, both theoretical and empirical, devoted to improving the predictability of volatility models. Brock and Hommes (1997) shows that some degree of predictability is possible when breaking down the sample period, incorporating new explanatory variables, or using a nonlinear model. White (2000) suggests a bootstrap-based reality check test to evaluate an out-of-sample forecast performance.

The most popular approach of forecasting volatility is the class of autoregressive conditional heteroscedasticity (ARCH) models originally introduced by Engle (1982). Bera and Higgins (1993) remark that: “A major contribution of the ARCH literature is the finding that apparent changes in the volatility of economic time series may be predictable and result from a specific type of nonlinear dependence rather than exogenous structural changes in variables.”

In this section, we will review the basic properties and development of the ARCH class models in volatility prediction.

Let  $r_t$  be the rate of return of a stock or portfolio from time  $t-1$  to time  $t$ .  $I_{t-1}$  denotes the information set available to the investor at time  $t$ , which contains all the public market information and relevant variable values up to time  $t-1$ . The expected return and volatility will be conditioned on the past information set. We define  $u_t$  and  $h_t$  as the conditional expected return and conditional variance of  $r_t$ , respectively. Thus,  $u_t = E[r_t|I_{t-1}]$ , and  $h_t = Var[r_t|I_{t-1}]$ . In this notation, any unpredictable return can be defined as the difference between  $r_t$  and  $u_t$ . We denote the unpredictable return as  $\xi_t$ , which can be interpreted as a collective measurement of news at time  $t$ . So a positive value of  $\xi_t$  implies an upward price

move, and it can be interpreted as a result of good news in the market, while a negative value of  $\xi_t$  suggests the release of bad news. Engle (1982) demonstrated that the conditional variance  $h_t$  can be modeled as a function of the past values of  $\xi_t$ . The general form of a  $p$ th order ARCH ( $p$ ) can be expressed as:

$$(3.5) \quad h_t = \omega + \sum_{i=1}^p \beta_i \xi_{t-i}^2,$$

where  $i = 1, \dots, p$ ;  $\beta$  and  $\omega$  are constants. The parameter  $\beta$  denotes the strength of the effects of a news shock  $i$  period ago on current volatility. The process is nonlinear in variance but linear in mean. By assuming a declining effect of news impact, we should expect a declining sequence of value of  $\beta_i$ .  $\xi_t$  is the innovation in the asset return. The ARCH model characterizes the distribution of the stochastic error  $\xi_t$  conditional on the realized values of the set of variables.

Due to the computational complexity associated with a higher order of the polynomials, Bollerslev (1986) generalizes the ARCH ( $p$ ) model to the GARCH model:

$$(3.6) \quad h_t = \omega + \sum_{i=1}^p \beta_i \xi_{t-i}^2 + \sum_{i=1}^q \gamma_i h_{t-i}.$$

A GARCH ( $q,p$ ) has the autoregressive GARCH term of order  $q$ , and a moving average ARCH term of order  $p$ . The GARCH (1,1) model implies that the effect of a return shock on current volatility declines geometrically over time, and Bollerslev (1992) show that it is preferred in most cases. Bera and Higgins (1993) show that the GARCH models have a set of desirable features, such as the ability to capture the heavy tails of financial data, and the simplicity and handling of nonlinearities. We compare the GARCH (1,1) model with other GARCH models with higher orders of  $p$  and  $q$ . For details on the comparison among different GARCH models, see the Appendix section.



The rest of the paper is organized as follows: Section 2 analyzes the modeling and estimating of intraday volatility using the High-Frequency Multiplicative Component GARCH model. Section 3 analyzes the interaction between overnight and intraday returns. Section 4 uses an event study methodology to examine the economic impact of food recalls on publicly traded firms asset returns. Section 5 concludes.

## 3.2 High-Frequency Multiplicative Component

### GARCH Model of Intraday Volatility

#### 3.2.1 High Frequency Multiplicative Component

##### GARCH Model

In this section, we analyze the High-Frequency Multiplicative Component GARCH model in the intraday volatility analysis. There has been a surge in the literature focusing on the choice of a volatility model and the criteria of defining a good volatility model. Engle and Patton (2001) outline some stylized facts about volatility that should be incorporated in a model. The basic features include pronounced persistence, mean reversion, sign of an innovation, and exogenous variables distortion.<sup>4</sup>

In contrast to the extensive research on interday stock market volatility models, the literature on intraday volatility is still relatively new. The availability of high-frequency data of the economy stimulates the research in higher frequency econometrics issues and their application to the economic and financial problems. In both economics and finance,

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<sup>4</sup>The first feature of intraday volatility is persistence. Since the 1960s, research shows that the clustering of large moves and small moves provides insight into the predictions of the future volatility patterns. Mandelbrot (1963) and Fama (1965) independently report evidence that large movements of the price of an asset tend to be followed by large movements, while small changes are often followed by small changes (Baillie (1996) and Schwert (1989)). The second feature is called mean reverting, which implies that, in general, there is a normal level of volatility to which volatility will eventually return. This can also be explained by the volatility clustering. Researchers are centering around the question of how to pick the level of a normal volatility and what is the real driving force behind this mean reverting. Mean reversion also implies that current information has no effect on long-term volatility forecasts. The third feature of volatility is called asymmetric effects of shocks. The shocks to the market can be included in the innovation term of the volatility model, and many models impose the assumption of asymmetric effects of positive and negative innovations on the conditional volatility. But the leverage effect or risk premium effect shows contradictory evidence that the sign of the innovation does matter in the predictability of a volatility model. For example, many researchers (Black (1976), Christie (1982), and Nelson (1991)) find evidence that volatility is negatively related to equity returns).

one measurement of progress in empirical research is the frequency of data used, from annual data to monthly data, to weekly data, to daily data, and now to intraday data. Engle (2000) gives the name *ultra-high-frequency* data to the limit case where every transaction is recorded. The research work done on the ultra-high-frequency data gives some new perspectives on the concept of volatility. In contrast to the estimation of expected returns, which generally requires long time records of data, the results of Merton (1980) suggest that volatility can be estimated arbitrarily well using sufficiently sampled high-frequency returns over any fixed time interval.<sup>5</sup> Data sampled at regular intraday intervals is summarized into a so-called realized volatility. In particular, Andersen and Bollerslev (1997) show that, under the usual diffusion assumptions, realized volatility computed from high-frequency intraday returns is effectively a consistent estimator of quadratic variation of the underlying diffusion process. This notion has gained enormous popularity due to its error-free volatility measure and simplicity of construction. Realized volatility is simply the sum of intraperiod high-frequency squared returns period by period. For example, for a 24-hour market, daily realized volatility based on 10-minute underlying returns is defined as the sum of the 144 intraday squared 10-minute returns on a daily basis.<sup>6</sup> Taylor and Xu (1997) decompose the conditional variance into two elements, the implied volatility and the realized volatility, using a hourly volatility model under an ARCH specification. The ARCH specification allows persistence in the variance structure and is proven to be effective in approximating several return series with similar magnitude cluster in chronological time. It is also used in explaining the fat tails and spiked peaks of empirical price change distributions.<sup>7</sup> In a seminal paper, Andersen and Bollerslev (1997) construct a 5-minute volatility model and apply it to a Deutschemark-dollar exchange rate and the S & P 500 index. They examine a multiplicative model of daily and diurnal volatility with an additional macroeconomic announcement component. Engle (2000) argues that Andersen and

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<sup>5</sup>See, among others, Nelson (1991) and Andersen and Bollerslev (1997).

<sup>6</sup>However, the data taken at higher frequencies is subject to all sorts of the so-called market microstructure noises, such as bid-ask bounce (Zhou (1996)), price discreteness, irregular spacing of quotes and transactions, etc.

<sup>7</sup>See Lamoureux and Lastrapes (1990), Epps (1976), among others.

Bollerslev's approach is not satisfactory for a number of reasons.<sup>8</sup> Many research has been done to capture the existence of long memory to high persistence in the process of volatility, such as the daily component model by Engle and Lee (1999), the Fractionally Integrated GARCH (FIGARCH), and Long Memory Stochastic Volatility Models (LMSV) by Breidt and DeLima (1998). In more recent research, Engle and Gallo (2003) propose to jointly consider absolute daily returns, daily high-low range, and daily realized volatility to develop a forecasting model based on their conditional dynamics.

The high-frequency data research not only improves the theoretical understanding of the econometric theory but also contributes to the practical application of financial models. For example, investors with liquidity constraints or short-term return targets will be able to adjust their market positions accordingly based on the prediction of intraday volatility models. However, even if the growing research on ultra high-frequency data and realized volatility has shed some light on volatility measurement and forecast, the key issue is to find appropriate model(s) to characterize the intraday price change and return variations. In other words, what is of interest is whether daily or other lower frequency models still generate promising results even when we increase the data sampling frequencies.

To set up the model, we first denote days in the sample by  $t(t = 1, 2, \dots, T)$ , and each day is further specified by tick-by-tick data points and indexed by  $i(i = 0, 1, \dots, N)$ . We take a new approach which is the tick-by-tick return measurement during the day. Thus, by definition the intraday return can be presented as:

$$(3.7) \quad r_{(t,i)}^I = \log \frac{P_{(t,i)}}{P_{(t,i-1)}},$$

where  $i = 1, 2, \dots, N$ .

Traditionally, return is calculated based on a preset interval, or referred to as bin, of

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<sup>8</sup>For details, see Engle and Patton (2001)

either a 5- or 10-minute interval.<sup>9</sup> However, our proposition is that such a regular interval division leads to biased and incomplete information due to a loss of data. The total number of observations in our sample is 20,906, which contains the tick-by-tick return on each trading day from 9:30 a.m. until 4:00 p.m. EST during the month of March 2007.<sup>10</sup> The advantage of including every trade quote is to recover full market information and helps us better understand the behavior of investors.

We specify the intraday return as the square root of the multiplicative product of daily return, diurnal return, and stochastic intraday return. Thus, the conditional variance can be decomposed into a multiplicative product of daily, diurnal, and stochastic intraday volatility. We use the following notation to denote intraday returns:

$$(3.8) \quad r_{(t,i)}^I = \sqrt{h_t d_t q_{(t,i)} \varepsilon_{(t,i)}},$$

where  $h_t$  is the daily variance component,  $d_t$  is the diurnal variance component after deflating the return by the daily volatility,  $q_{(t,i)}$  is the stochastic intraday volatility component with mean equal to one, and  $\varepsilon_{(t,i)}$  is an error term that is assumed to follow the standard normal distribution.

### 3.2.2 Empirical Estimation

Unlike the abundance of past literature that has examined the modeling strategy on intraday volatility, there has been very little research attention devoted to the empirical application of those theoretical models. In this section we will discuss data sampling and the estimation process of the High-Frequency Multiplicative Component GARCH model. Transactions data can be characterized by two random variables: the time of the transaction, and the observation at that time of the transaction. In point processes literature, the point of time is referring to the time when a contract to trade a certain number of shares of a

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<sup>9</sup>Engle chose a 10-minute interval for the bin size. The literature shows that a 5-minute interval generally outperforms other interval sizes. In Engle's paper he named the variance within each bin after deflating the daily effects as diurnal (calendar) components.

<sup>10</sup>If the data are sampled at 10-minute intervals, the size of the sample decreases to 40 records per day and 880 data points in total. Another common practice in empirical high-frequency data research is to use 5-minute intervals, which gives a total of 80 data points per day and 1,760 in total for March 2007.

stock is agreed upon; and the observations are usually called marks, which may include the volume of the contract, the price of the contract, and the posted bid and ask prices. For the purpose of this paper, we use the consolidated trades data from the trade and quote (TAQ) database in the intraday volatility analysis.<sup>11</sup>

For daily data we use the Center for Research in Security Prices (CRSP) database.<sup>12</sup>

For the High-Frequency Multiplicative Component GARCH model, we select Sara Lee Corporation (Ticker: SLE). Based in Downers Grove, Illinois, the Sara Lee Corporation (SLE) is a global manufacturer and marketer of high-quality, brand-name products for consumers throughout the world. Sara Lee's businesses include fresh bakeries, and household body care throughout North America and around the globe.

Figure 3.1 plots price, volume, and return charts of SLE during the trading days from March 1 to March 31, 2007. The price chart shows that the price of the stock is more volatile during the second half of the day, especially during the market closing period. When we consider the price chart and volume chart together, we notice that the two spikes of the volume happened after the stock price touched the two lowest points during the month. This might serve as an indication of the investors trying to take advantage of the lower cost of the shares. The largest volume, 1,066,800 shares, happened on March 16 at 9:30:20 at the price of \$16.64. The second largest trading, 621,500 shares, traded on March 5 at 16:02:50 at the price of \$16.42, after the stock price hit the lowest level at \$16.17 at 10:02:27 on March 5. The third largest trading happened on March 16 at 16:02:50 at the price of

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<sup>11</sup>The trade and quote (TAQ) database contains intraday transactions data (trades and quotes) for all securities listed on the NYSE and American Stock Exchange (AMEX), as well as NASDAQ National Market System (NMS) and Small Cap issues. In microstructure models, trades may reflect private information that is then incorporated into new quotes and the following trades. A trade is a transaction price when a deal is agreed upon between counterparties. A quote reflects a market participant's willingness to trade. In financial markets, traders buy and sell assets and specialists post quotes. Traders observe the quotes and previous trades to determine their trading strategies and the new trades. Similarly, specialists observe previous quotes to decide what quotes to post. Engle and Lunde (2003) examine speed of the information flow between trades and quotes using a bivariate point process. They find that prices respond more quickly to trades when information is flowing and the price impacts of trades are high in such circumstances. This paper chooses trades and excludes quotes in the database.

<sup>12</sup>CRSP is a research center at the Graduate School of Business of the University of Chicago. It maintains the most comprehensive collection of security price, return, and volume data for the NYSE, AMEX and NASDAQ stock markets. Founded in 1960 by James H. Lorie and Lawrence Fisher, professors at the University of Chicago Graduate School of Business, CRSP was set up in order to advance research in operations of security markets. It is the first organization to have compiled accurate and computerized information, and to have made the data available to academic and commercial markets.

FIGURE 3.1

Tick-by-Yick Price, Volume, and Return of SLE

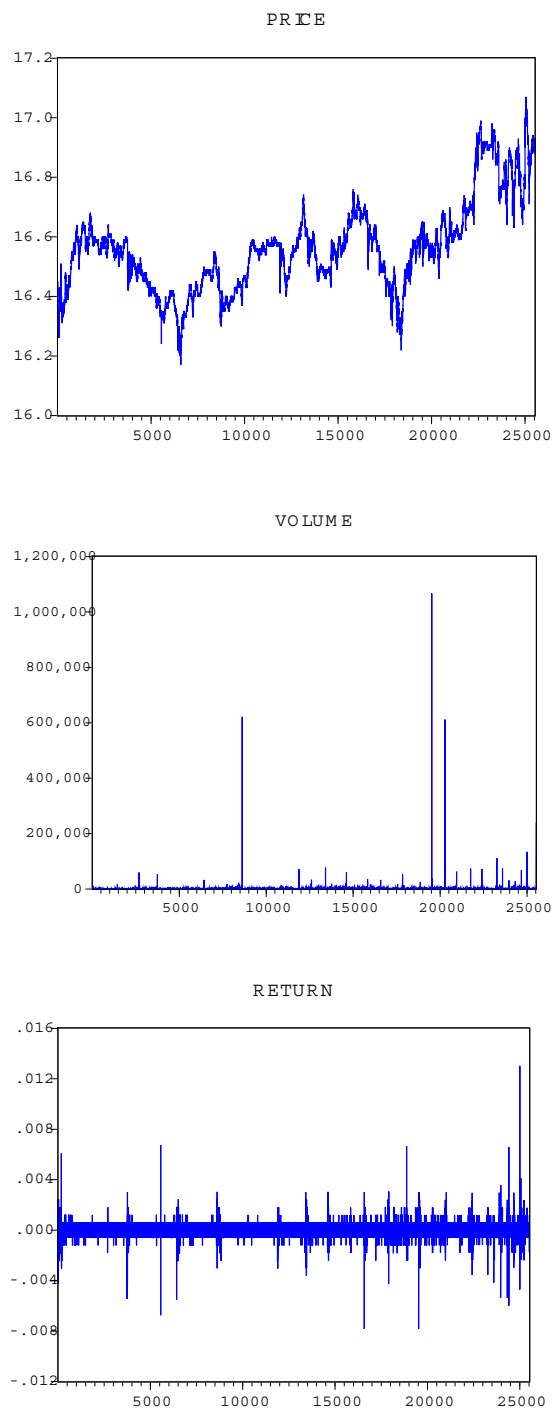


TABLE 3.1

## Descriptive Statistics for Price, Return, and Volume

	Obs.	Mean	Std. Dev.	Min.	Max.	Median	Kurtosis	Skewness
Price	20,906	16.54	.138	16.17	17.03	16.54	.946	.757
Return	20,905	.000	.000	-.008	.008	.000	22.996	-.383
Volume	20,906	675.289	6619.478	100.000	621,500.000	200.000	7268.401	80.248

\$16.61. Table 3.1 shows the descriptive statistics of these three variables, price, volume, and return. As expected, we can see that when every trade is recorded, the variation in returns decreases dramatically.

We take a three-step approach to decompose intraday equity returns into three components, daily variance, diurnal variance, and intraday variance. In the first step we estimate the daily volatility component,  $h_t$ . The most popular approach of forecasting daily volatility is the class of autoregressive conditional heteroscedasticity (ARCH) models originally introduced by Engle (1982). Bollerslev (1992) provide a nice survey of the ARCH and related models applied to financial time-series. After the original ARCH model introduced in 1982 by Engle, Bollerslev (1986) generalizes the ARCH (p) model into the GARCH (p,q) model:

$$(3.9) \quad h_t = \omega + \sum_{i=1}^p \beta_i \varepsilon_{t-1}^2 + \sum_{i=1}^q \gamma_i h_{t-i},$$

where  $\omega$ ,  $\alpha$ , and  $\beta$  are constant parameters. The survey by Bollerslev (1992) shows that the GARCH(1,1) is preferred in most research. GARCH (1,1) is the simplest form that assumes a geometrically decline of the effect of a return shock on current volatility over time. In this case, the estimated daily variance term is:

$$(3.10) \quad \hat{h}_t = \omega + \beta \varepsilon_{(t-1)}^2 + \gamma h_{(t-1)}.$$

In the second step, we estimate the diurnal variance component,  $d_t$ . Based on the multiplicative component form of the daily volatility model, we have:

$$(3.11) \quad \frac{r_{(t,i)}^2}{h_t} = d_t q_{(t,i)} \varepsilon_{(t,i)}^2$$

$$(3.12) \quad E\left[\frac{r_{(t,i)}^2}{h_t}\right] = d_t E[q_{(t,i)}]$$

$$(3.13) \quad E\left[\frac{r_{(t,i)}^2}{h_t}\right] = d_t$$

given assumption that the mean of stochastic volatility,  $E[q_{(t,i)}]$ , equals to one. Let

$$(3.14) \quad y_{(t,i)} = \frac{r_{(t,i)}}{\sqrt{\hat{h}_t}} = \sqrt{d_t q_{(t,i)}} \varepsilon_{(t,i)},$$

then the diurnal component can be estimated as the variance of  $y_{(t,i)}$  on day  $t$ , which is denoted as:

$$(3.15) \quad \hat{d}_t = \frac{1}{T} \sum_{t=1}^T y_{(t,i)}^2, i = 1, 2, \dots, N.$$

In the final step we estimate the stochastic intraday volatility using a GARCH(1,1) model. Let:

$$(3.16) \quad z_{(t,i)} = \frac{r_{(t,i)}}{\sqrt{\hat{h}_t \hat{d}_t}},$$

which is the normalized daily return after deflating by daily return and diurnal return. Given the assumptions on conditional moments

$$(3.17) \quad z_{t,i} | I_{t,i-1} \sim N(0, q_{(t,i)}),$$

where  $I_{t,i-1}$  represents all the information available up to the current moment at tick  $i$  on day  $t$ . The estimated intraday volatility can be estimated from a standard GARCH(1,1)



model:

$$(3.18) \quad q_{(t,i)} = \omega + \beta_i z_{(t,i-1)}^2 + \gamma_i q_{(t,i-1)}.$$

The daily variance component,  $h_t$ , can be estimated in many different ways. Engle and Gallo (2003) used a daily realized variance approach. Engle and Chanda (2005) utilize commercially available volatility forecasts produced daily. Andersen and Bollerslev (1997) propose a daily GARCH model for monthly data. The daily return data contain the daily return for SLE each day in March from 1947 to 2007. The daily variance is calculated using a GARCH (1,1) model. Our research shows that GARCH (1,1) model outperforms other GARCH models. For a detailed comparison, see Table A.1 in the Appendix. The estimation result of the model is:

$$(3.19) \quad \hat{h}_t = 0.000 - 0.191\varepsilon_{(t-1)}^2 + 1.163h_{(t-1)}.$$

The ARCH term,  $\varepsilon_{(t-1)}^2$ , represents news about volatility from the previous period, and the GARCH term,  $h_{(t-1)}$ , shows last period's forecast variance. In a financial context, an agent or trader predicts the current period's variance by forming a weighted average of three terms: a long-term average, the forecasted variance from the last period, and information about volatility observed in the previous period. The estimated parameter of  $h_{(t-1)}$  indicates a persistent impact of last period's forecast variance and is consistent with the volatility clustering often seen in financial returns data, where large changes in returns are likely to be followed by further large changes.

The diurnal component,  $d_t$ , is calculated in a different way from the Engle (1982)'s method. Since we use the tick-by-tick data without dividing the data into fixed intervals, we calculate the variance of returns on each day after deflating by the daily volatility.

After normalizing returns by daily and diurnal volatility components, we model the residual volatility as a GARCH (1,1) process.

Table 3.2 summarizes the estimation results of the daily and diurnal variance components of the High-Frequency Multiplicative Component GARCH model. Table 3.3 shows the estimation results for the intraday component of the GARCH model after filtering out daily and diurnal results. Our research finds that GARCH (1,1) model has a better performance compared to other GARCH specifications. For a detailed comparison see Appendix Table A.2. The estimate of  $\beta$  for the GARCH model is .093, with a standard error of .002, and estimate for  $\gamma$  is .843, with a standard error of .004. This indicates a strong relation between last period's forecast variance and the estimate of volatility for this period's variance. To assess the persistence implied by the GARCH model, it is useful to consider the sum of  $\beta$  and  $\gamma$ , which must be less than 1.0 for the volatility process to be stationary. This sum equals .969 for the March 2007 sample period for Sara Lee stock.

We apply a similar procedure at the industry level during the same time period. Tables 3.4, 3.5, and 3.6 show the intraday volatility analysis results for three sectors: food retails and wholesales, restaurants and bars, and food products in three exchanges: NYSE, Pacific Exchange, and NASDAQ.<sup>13</sup> The persistence parameters are .983, .988, and .957, for the Food Retailers and Wholesalers, Restaurants and Bars, and Food Products sectors, respectively. This shows that even after removing the daily volatility component, the intraday volatility component still demonstrates a long persistence.<sup>14</sup> Estimation results show that stocks listed in NYSE have a higher estimation for  $\gamma$ , which is the persistence parameter for last period's forecast volatility, than stocks listed in the other two stock exchanges, Pacific and NASDAQ. But for the estimation of  $\beta$ , the estimation on the news about volatility from the previous period, there is no clear pattern as to which exchange yields a better estimation results. The estimation results on the summation of  $\beta$  and  $\gamma$  show that in the food retails and wholesales sector, and restaurant and bars sector, the NYSE group also

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<sup>13</sup>The Industry Classification Benchmark is comprised of 10 industries, 18 supersectors, 39 sectors and 104 subsectors. Food products is a subsector of food producers under the supersector food and beverage in the consumer goods industry. Food retailers and wholesalers is a subsector of food and drug retailers under retails supersector in the consumer services industry. Restaurants and bars is a subsector in the travel and leisure sector under the travel and leisure supersector in the consumer services industry.

<sup>14</sup>The family of GARCH models is estimated using the maximum likelihood method. The log-likelihood function is computed from the product of all conditional densities of the prediction errors.

TABLE 3.2

Estimation Results of Daily Variance and  
Diurnal Variance Components for SLE

Date	$\hat{h}_t$	$\hat{d}_t$
20070301	8.36E-05	0.00224
20070302	8.31E-05	0.00259
20070305	8.65E-05	0.00233
20070306	8.58E-05	0.00189
20070307	8.61E-05	0.00231
20070308	8.46E-05	0.00272
20070309	8.32E-05	0.00259
20070312	8.54E-05	0.00186
20070313	8.39E-05	0.00370
20070314	8.88E-05	0.00364
20070315	8.82E-05	0.00391
20070316	8.84E-05	0.00502
20070319	8.67E-05	0.00325
20070320	8.51E-05	0.00273
20070321	8.47E-05	0.00401
20070322	8.54E-05	0.00346
20070323	8.39E-05	0.00444
20070326	8.23E-05	0.00471
20070327	8.08E-05	0.00489
20070328	7.95E-05	0.00857
20070329	7.83E-05	0.00601
20070330	7.72E-05	0.00863

TABLE 3.3

Estimation Results of Intraday  
Component for SLE

Parameters	Estimates
$\omega$	0.064** (.002)
$\beta$	.093** (.002)
$\gamma$	.843** (.004)
$\beta + \gamma$	.969

TABLE 3.4

Estimation Results of Intraday Component for the Food Retailers and Wholesalers Sector

	NYSE	Pacific	NASDAQ
$\omega$	.000 (.000)	.000 (.001)	.000 (.000)
$\beta$	.166** (.002)	.258** (.021)	.190** (.003)
$\gamma$	.817** (.001)	.679** (.000)	.761** (.002)
$\beta + \gamma$	.983	.937	.951

TABLE 3.5

Estimation Results of Intraday Component for the Restaurant and Bars Sector

	NYSE	Pacific	NASDAQ
$\omega$	.000 (.000)	.000 (.000)	.000 (.001)
$\beta$	.182** (.001)	.256** (.022)	.240** (.001)
$\gamma$	.806** (.020)	.702** (.001)	.732** (.003)
$\beta + \gamma$	.988	.958	.972

TABLE 3.6

Estimation Results of Intraday Component for the Food Products Sector

	NYSE	Pacific	NASDAQ
$\omega$	.000 (.000)	.000 (.002)	.000 (.001)
$\beta$	.234** (.006)	.249** (.023)	.271** (.001)
$\gamma$	.713** (.001)	.702** (.002)	.644** (.002)
$\beta + \gamma$	.947	.951	.915

reports a stronger persistence than the other two stock exchanges. This can be explained by the size and market depth of the exchanges.

One of the major improvements of the ARCH and GARCH models is to incorporate the so-called *leverage or asymmetric effect* to capture the effects of news shock in time series data. The leverage or asymmetric effect is first introduced by Black (1976) and confirmed by French and Stambaugh (1987), Nelson (1991), and Schwert (1990). In ARCH and GARCH models, it is assumed that good news and bad news affect the predictable volatility in a similar way. But empirical results show that such a symmetry constraint on the conditional variance function in past  $\varepsilon$ 's is inappropriate. This is because empirical research shows that there is a larger effect on the predictable volatility when a negative shock occurs due to bad news compared to a positive shock associated with good news. The so-called “asymmetric” or “leverage” volatility models are introduced to address the issue of different predictability for future volatility due to good news and bad news. So far most research focuses on interday volatility changes associated with this asymmetric effect.<sup>15</sup>

### 3.3 Interaction Between Intraday Return and Overnight Return

#### 3.3.1 Information and Volatility

As we discussed in the introduction, overnight return is defined as the log-price difference between the previous day's closing price and today's opening price. Some researchers argue that the volatility feature is interrupted due to the flow of information released when the market is closed. The effect of news on the price change are different during the trading time and the closing time.<sup>16</sup> The overnight return captures the accumulated information effects on market prices when the equity market is closed. That is:

$$(3.20) \quad r_{(t,i)}^O = \log \frac{O_t}{C_{t-1}}, t = 1, 2, \dots, T.$$

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<sup>15</sup>See the first systematic comparison of volatility model by Pagan and Schwert(1990), Exponential GARCH model by Nelson (1991), and Engle (2000), among others.

<sup>16</sup>See Romer (1993), Dow and Gorton (1993).

Measuring and testing the news impact on volatility abound in recent years, especially in macroeconomics and finance. Both theoretical approaches and empirical applications are aimed at improving the volatility predictability in the presence of news.<sup>17</sup> The first part of this section discusses about the effects between information and return volatility, and the second part utilizes a linear model to study the dynamics between overnight return and intraday return.

The link between information and prices is a popular subject of the finance literature. Researchers find the power of public information and order flow in explaining the price volatility. Grossman and Stiglitz (1980) propose a model where prices convey information flow from the informed to the uninformed. When informed individuals obtain positive news about a certain stock, they post a higher bid, and the price of that stock increases. So the price system makes the information previously owned by the informed investors publicly available to the uninformed. Based on Grossman and Stiglitz's (1980) research, Glosten and Milgrom (1985) extend the contents of order flow to include both public and private information, as well as market shocks from either rational or irrational trades.<sup>18</sup> In general, the deviation of the stock price from its fundamental value is a result of information effects, rational and irrational investor behavior, and other market microstructure frictions.

One focus of this paper is to analyze trading versus nontrading period stock market return. Fleming, Kirby, and Ostdiek (2006) summarize the major challenges in this area: the endogeneity of the information generation process (i.e., the mix of information-driven price

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<sup>17</sup>The so-called "asymmetric" or "leverage" volatility models take into account the different predictability for future volatility between good news and bad news. Pagan and Schwert (1990) introduce the first comparison of volatility models with an emphasis on the asymmetric effect of positive and negative news on volatility. Further, research led by Engle and Ng (1993) provides news diagnostic tests and a nonparametric model for uncovering the relations between news and volatility and how to interpret the difference among different volatility models. In a classic paper by Gallo, he refers to the price change at opening time as *transitory volatility* and claims that this volatility declines during the day. This finding is also confirmed by other researcher. See Mitchell and Mulherin (1994), Stoll and Whaley (1990), among others. In Gallo's paper, he is particularly interested in the question as to whether the close-to-open (overnight returns) has a statistically significant impact on the open-to-close (intraday returns). The investigation of overnight surprises is of particular interest for trading in segmented markets. A growing number of literature has shown that there is an asymmetry of behavior originating from two different sources: one from the accumulation of news during the close hours, and the other from the news released when the market is open and active trading is available.

<sup>18</sup>Rational trades refer to the noninformation-based liquidity trades, and irrational trades are trades based on market noise. See Black (1976).

adjustment and price error), inability to observe the investors' motivation, and multieffects of market structure. Dow and Gorton (1993) claim that the trading process itself is the mechanism for information exchange, and stock return variances are higher during trading hours than during nontrading hours, and longer trading hours are associated with higher trading volume (Oldfield and Rogalski (1980), French and Roll (1986), Meese and Rose (1991)). Recent empirical work suggests that the arrival of new information and the price change may not follow a clear pattern. For example, Cutler, Poterba, and Summers (1991) find that even the largest daily price changes cannot be associated with any significant market news, especially at the individual firm level, where private information takes a larger role in price change. Berry and Keith (1991) study the number of news items released by Reuter's News Service as proxies for the public information flow, and results show little evidence of such information in explaining the variation of daily volatility. As pointed out by Goodhart and O'Hara (1997), the private information-based explanation for the volatility behavior should be able to address the empirical return volatility issue within the trading day, within the trading week, and over off-trading periods as well. So far most of the empirical work has studied the interdaily volatility pattern, the intraday volatility pattern, and the announcements in isolation (Andersen and Bollerslev (1997)). Andersen and Bollerslev (1997) take a step in this direction and perform a comprehensive study of the volatility process in the DeutscheMark-dollar foreign exchange market based on a one-year sample of 5-minute returns using Reuters interbank quotes data. Their research finds that the largest returns appear to be linked to the release of public information, especially certain macroeconomic announcements, namely the employment reports, gross domestic product, trade balance figures and other news related to the real economy. However, the explanatory power is less evident at the lower frequency level. Given the fast development of communication channels and tools, it is difficult to pin down the time regarding to a specific news release. In this paper we distinguish the news release between the time period when the market is open and when the market is closed. Based on our literature survey, our research is among the pioneer work in exploring the effects of recall news on the food

industry stock price change.

Another implication of the effects of information on volatility is the intraday U-shaped pattern.<sup>19</sup> The source of the intraday U-shaped pattern has been extensively studied in volatility research. An explanation for the intraday U-shaped volatility pattern falls into two categories: asymmetric information, and market structure. The first argument says that private or asymmetric information is the central factor as investors optimize their trading portfolio return while minimizing the trading costs and market uncertainties. The second argument focuses on the impact of market structure, claiming that the intraday patterns occur because of a long-term horizon of the strategic behavior of the investor. Admati and Pfleiderer (1988) suggest that the trading clustering at the opening and closing of trading is due to the asymmetric information about the future cash flows of a stock. Their central argument is that volume patterns are due to the simultaneous trading of both informed and uninformed investors with the intention to minimize the transaction costs. Brock and Hommes (1997) generalize the case where investors can have different optimal holding portfolios when the market is closed from the case of when the market is open. Their research shows that it is the periodic market closure that attributes to the U-shaped pattern. They argue that the demand for trading at the open and close of the market is relatively strong and inelastic compared to the interday as traders try to optimize investment portfolios and diversify overnight risks. Brock and Kleidon's work is based on the assumption of some degree of monopoly power of market makers. When the market opens and before they can estimate the true price level of the stock, market makers tend to construct a wide bid-ask spread so they will not be adversely selected by those who possess more information. As the market approaches closing, market makers maintain wide bid-ask spreads in order to minimize their excess exposure to the risk of holding unwanted inventories when the market shuts down.

In general, there are two causes that lead to the U-shaped intraday volatility pattern. First, investors want to rebalance their portfolio when the market states change between

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<sup>19</sup>The U-shaped pattern is also referred to as the reverse J-shaped or the intraday "smile" pattern. Literature shows that this pattern exists in intraday price, volume, and returns.



closing and opening. Second, investors are constantly reevaluating their positions when facing and competing with both informed and uninformed traders. Research also shows that order flow is a major component of the transmission mechanism from information to prices.<sup>20</sup> In this paper, our analysis, based on the intraday stock price of the food sectors, reveals a J-curve intraday price pattern instead of a U-shaped one.

### 3.3.2 Dynamics of Intraday Return and Overnight Surprises

Market volatility has been found to be higher during the trading rather than the non-trading hours (French and Roll (1986), Amihud and Mendelson (1987), and Wood, McInish, and Ord (1985)). In this section we will focus on the issue of the dynamic relationship between the intraday return and overnight surprises. Research shows that overnight surprises have an impact on the intraday conditional variance and mean. But our research on the food sector data during the year of 2007 does not reveal such a relationship in general except for the food products sector. This paper also studies whether yesterday's intraday return volatility has a "hang-over" effect on the overnight return volatility. The impact of food recall is related to event studies in Finance and Economics. Since Dolley (1933)'s research on the price effects of stock splits, event studies have improved both in terms of methodology and empirical applications. In the late 1960s, Ball and Brown (1969) applied the event study methodology in the case of information content of earnings, and Fama (1965) introduced the modern event study methodology and used it in the effects of stock splits. It provides further information on the interaction between the trading hour return and the nontrading hour return.<sup>21</sup>

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<sup>20</sup>Brown and Warner (1985) find that the order flow on the NYSE follows a U-shaped intraday pattern. Lee and Liu (2001) show that the clustering of trading at the open and close of trading can be found in both informed and uninformed traders in the Taiwan stock exchange

<sup>21</sup>The arguments of Fama (1965) form the theoretical foundation for the Efficient Market Hypothesis, which reasons that in an efficient and active market consisting of many well-informed investors, equity prices will appropriately reflect the effects of information based on present and future expected events. The cornerstone of the improvement is the separation of common shocks or confounding events out of the general stock market price movements. Other modifications are related to adjustments in the experimental design to accommodate the violation of statistical assumptions and to include more specific hypotheses. This paper focuses on the dynamics between overnight and intraday return.

Using a simple least-square estimation, we have:

$$(3.21) \quad r_{t,i}^I = a_1 + b_1 r_t^O + \xi_t$$

$$(3.22) \quad r_t^O = a_2 + b_2 r_{t-1,i}^I + \eta_t.$$

In the estimation process, we choose the top ten most actively traded stocks in three food-related sectors from January 1 to December 31, 2007. First, we estimate the effects of overnight return on the intraday return for each of the three sectors.

Contrary to most research results, the OLS estimation results do not suggest a strong relation between the overnight and the intraday returns in general. Table 3.7 shows the sample estimation results for the food retailers and wholesalers sector. Except for one company, United Natural (UNFI), that demonstrates a negative impact of the overnight return on intraday return, the rest of the ten actively traded firms does not show a strong relation between the previous day's overnight return and the next day's intraday return. The parameter estimate shows that when there is a 1% increase in the overnight return, the intraday return will decrease by .542%. Table 3.8 shows the results for the restaurant and bars sector. We find mixed results for firms that indicate an explanatory relation between the overnight and intraday returns. Starbucks (SBUX), McDonalds (MCD), and Burger King Holdings, Inc. (BKC) indicate a negative impact of overnight return on intraday return, while Darden Restaurant (DRI) shows a positive effect of the overnight return on the intraday return. The negative relation for SBUX can be interpreted in the same way as the stock for UNFI. The positive estimation result on DRI shows that when the overnight return increased by 1%, the intraday return will increased by .262%. Interestingly, in the food products sector, which is reported in Table 3.9, we find that over one-half of the firms are responsive to the overnight return. Among the top ten most actively traded firms, Kraft Foods Inc (KFT), Conagra Foods (CAG), SaraLee Corporation (SLE), Smithfield Foods (SFD), HJ Heinz (HNZ), and Pilgrim's Pride (PPC) show a strong negative relation between overnight and intraday returns. This result indicates that a positive overnight return has a negative impact on the intraday return. The negative relationship can be

TABLE 3.7

Estimation Results of Overnight Return Effects for  
the Food Retailers and Wholesalers Sector

	KR	SYT	SWY	SVU	WFMI	RDK	CASY	WMK	GAP	UNFI
$a_1$	.001 (.001)	.000 (.001)	.000 (.001)	.000 (.001)	.000 (.001)	.001 (.001)	.000 (.001)	-.001 (.001)	.001 (.001)	.000 (.002)
$b_1$	.054 (.105)	-.280 (.121)	-.127 (.129)	.163 (.132)	.145 (.132)	.154 (.136)	-.053 (.107)	.216 (.161)	-.176 (.128)	-.542** (.149)

TABLE 3.8

Estimation Results of Overnight Return Effects for  
the Restaurant and Bars Sector

	SBUX	MCD	YUM	DRI	CAKE	EAT	SONC	BKC	RT	TXRH
$a_1$	-.002 (.001)	.001 (.001)	.000 (.001)	.000 (.000)	-.002 (.001)	.000 (.001)	-.002 (.001)	.000 (.001)	.001 (.001)	.000 (.001)
$b_1$	-.275** (.088)	-.257** (.113)	-.026 (.019)	.262** (.082)	-.036 (.092)	-.013 (.132)	.212* (.111)	-.350** (.125)	.123* (.070)	.023 (.111)

interpreted to show that the return pattern could reverse overnight based on our sample.

Next we analyze the effect of previous day's intraday return on the overnight return in these three food sectors. The OLS estimation results are reported in Tables 3.10, 3.11, and 3.12. Our empirical results in general do not indicate a strong relation between these two variables. However, in the food retailers and wholesalers sector, except for two stocks, Super Value Inc (SVU), Casey's General (CASY), and United Natural (UNFI), which show a neg-

TABLE 3.9

Estimation Results of Overnight Return Effects for  
the Food Products Sector

	KFT	ADM	CAG	SLE	TSN	SFD	GIS	HNZ	BG	PPC
$a_1$	.000 (.001)	.000 (.001)	-.001 (.001)	.000 (.001)	-.001 (.001)	.000 (.001)	.000 (.001)	.000 (.001)	-.005 (.002)	-.003 (.002)
$b_1$	-.485** (.135)	-.036 (.094)	-.321** (.097)	-.448** (.111)	-.163* (.086)	-.276 (.134)	-.186* (.106)	-.316 (.106)	-.062 (.059)	-.314** (.130)

TABLE 3.10

Estimation Results of Intraday Return Effects for  
the Food Retailers and Wholesalers Sector

	KR	SYW	SWY	SVU	WFMI	RDK	CASY	WMK	GAP	UNFI
$a_2$	.000 (.001)	-.001 (.000)	.000 (.001)	.000 (.000)	.000 (.001)	.001 (.001)	.001 (.000)	.000 (.001)	.000 (.001)	-.001 (.001)
$b_2$	-.022 (.038)	.033 (.033)	.016 (.031)	-.064** (.030)	-.057 (.036)	-.045 (.029)	-.082** (.037)	-.021 (.025)	.015 (.031)	-.058** (.026)

TABLE 3.11

Estimation Results of Intraday Return Effects for  
the Restaurant and Bars Sector

	SBUX	MCD	YUM	DRI	CAKE	EAT	SONC	BKC	RT	TXRH
$a_2$	.001 (.001)	.001 (.000)	-.002 (.003)	.000 (.001)	.000 (.001)	.000 (.001)	.000 (.001)	.001 (.001)	.001 (.001)	.001 (.001)
$b_2$	.054 (.105)	-.078** (.035)	.199 (.210)	-.038 (.048)	-.002 (.044)	-.073** (.030)	-.001 (.036)	.010 (.032)	.050 (.058)	-.066* (.036)

ative relation between intraday and overnight returns, the rest of the top ten actively traded stocks do not show a significant relationship. Similar results are found in the restaurant and bars sector, where only two firms, McDonalds (MCD) and Sonic Corporation (SONC), show a negative impact of the previous day's intraday return on the overnight return. In the food products sector, Kraft Foods (KFT) and Conagra Foods (CAG) yield a negative relation between the previous day's intraday return and the overnight return.

Our research does not find a significant interaction effect between overnight and intraday returns based on the most actively traded stocks and FDA (Food and Drug Administra-

TABLE 3.12

Estimation Results of Intraday Return Effects for  
the Food Products Sector

	KFT	ADM	CAG	SLE	TSN	SFD	GIS	HNZ	BG	PPC
$a_2$	.000 (.000)	.001 (.001)	.001 (.000)	.000 (.000)	.000 (.001)	.000 (.001)	.000 (.000)	.000 (.000)	.000 (.002)	.002 (.001)
$b_2$	-.114** (.028)	.005 (.043)	-.103** (.040)	.000 (.035)	-.074 (.046)	-.013 (.030)	-.052 (.038)	-.051 (.037)	-.087 (.068)	-.011 (.031)

TABLE 3.13

Estimation Results of Overnight Return Effects for  
the Tyson Company and Kraft Foods Global Company

Estimate	TSN	KFT
$a_1$	.002 (.003)	.001 (.003)
$b_1$	-0.405 (.443)	-.310 (0.423)

tion) recall data. This may serve as a symptom that overnight news or surprises do not have a significant impact on the price change when the market is open. Finally, we investigate the effects of USDA food recall cases and their impacts on two specific companies involved in the food recall cases. The first recall is Tyson Fresh Meats Company's recall of 16,743 pounds of ground beef that may be contaminated with E. coli O157:H7 on March 2, 2007. Tyson's voluntary recall is a Class I recall and health risk is high. The second recall is Kraft Foods Global, Inc's recall of approximately 1,800 pounds of bacon due to insufficient cooling during processing. Kraft's voluntary recall is a Class II recall and health risk is low. The time span is five days before and five days after the recall for each firm. For Tyson, the data window is from Feb. 26 to March 9 and for Kraft, the time frame is March 21 to April 2. First, we analyze the effects of overnight return on the intraday return. The results in Table 3.13 show a negative impact of the overnight return on the intraday return but the value of the impact is statistically significant. Table 3.14 indicates a negative relation between the previous day's intraday and overnight returns for TSN stock and a positive relation for KFT stock. However, both of these two effects are statistically insignificant.

### 3.4 An Event Study of Food Recall

The impact of food recall is receiving growing interest in financial and agricultural literature. A number of studies have examined the effect of food recall. In order to commence our investigation of the food recall event analysis, we would like to provide some of its background information. A recall is an effective method of removing from commerce any

TABLE 3.14

Estimation Results of Intraday Return Effects for  
the Tyson Company and Kraft Foods Global Company

Estimate	TSN	KFT
$a_2$	.000 (.001)	-.000 (.001)
$b_2$	-.112 (.079)	.031 (.068)

product that may be adulterated or misbranded. The Food Safety and Inspection Service (FSIS) within the USDA gives the following definition of a food recall: “A food recall is a voluntary action by a manufacturer or distributor to protect the public from products that may cause health problems or possible death.” FSIS inspects and regulates meat, poultry, and processed egg products produced in federally inspected plants. FSIS is responsible to make sure that these products are safe, wholesome, and accurately labeled. The other food recall regulation agency in the United State is the Department of Health and Human Services’ FDA. FDA regulates food, pet, and farm animal feed.

Recalls are generally initiated by the manufacturer or distributor of meat, poultry, and processed egg products, sometimes at the request of FSIS. Under the current FSIS regulation, all recalls are voluntary, and firms such as a manufacturer, distributor, or importer, take these actions as part of their responsibility to protect the public’s health and welfare. But if a company refuses to recall its products in the case of a recall accident, then FSIS has the legal authority to detain and seize those products in commerce.<sup>22</sup>

Our purpose is to assess the economic impact of recalls on a company’s asset returns in the stock market. Measuring the overall effect of recall on stock return is problematic, and a direct measurement of the impact of a recall on a firm’s profitability or stock price is impossible. In addition, because the recall accrues over time, current stock price may not

<sup>22</sup>According to the FSIS recall regulation policy, there are four primary causes that will bring the attention of FSIS on meat and poultry products: products with potential hazard reported by the manufactures or distributors; adulterated or misbranded products discovered by the FSIS sampling program; unsafe or improperly labeled foods in the course of routine duties of FSIS field inspectors; unsafe, unwholesome, or inaccurately labeled food submitted by state or local public health departments.

accurately reflect the true economic impact of a given recall announcement. This difficulty drives us to use an alternative measure, which is the abnormal return of a firm in the case of a recall. This event study methodology is widely used in a variety of disciplines, such as finance, accounting, marketing, law, and organizational behavior. Event study measures the magnitude of the effect that an unexpected event has on the expected return and risk of a firm or firms associated with that particular event. Based on the Efficient Market Hypothesis,<sup>23</sup> the price of a stock is the present value of a firm's expected cash flows at any given time and it reflects all the current available information about the firm's present and future earnings potential. Under the assumption of the Effective Market Hypothesis, the stock price changes as soon as the market receives any new information resulting from an unexpected event. Brown and Warner (1985) argue that the amount of change in the price of a stock after an event, relative to its pre-event price, would reflect the unbiased market estimate of the economic value of that event. Abnormal return is used to measure the change in stock price after adjustment for normal market movements.

The daily returns of an individual stock  $i$  are calculated as:

$$(3.23) \quad R_{i,t} = \ln(P_{i,t+1}) - \ln(P_{i,t})$$

$$(3.24) \quad R_{m,t} = \ln(P_{m,t+1}) - \ln(P_{m,t}),$$

where  $P_{i,t}$  and  $P_{m,t}$  represent the closing price for stock  $i$  and the S&P 500 index on day  $t$ , respectively. We use the same method in calculating market index returns. To calculate the abnormal returns for each firm in the event period, we use the market model by MacKinlay (1997). The return for any stock  $i$  on day  $t$  is:

$$(3.25) \quad R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

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<sup>23</sup>See Fama (1965) for more details.

where  $R_{i,t}$  and  $R_{m,t}$  represent the returns on stock  $i$  and market index return on day  $t$ , respectively. For our research purposes, the event day is the date when the announcement of a recall is first released from the FDA or USDA.<sup>24</sup>

Let  $\tau$  be used to index returns throughout the event period, where  $\tau = 0$  represents the event day,  $\tau = t_1$  to  $\tau = t_0$  constitutes the estimation window, and  $\tau = t_2$  to  $\tau = t_1$  is defined as the event window. So by definition,  $T_1 = t_1 - t_0$  represents the estimation window and  $T_2 = t_2 - t_1$  denotes the event window. In order to reduce bias for the impact of the food recall event, the estimation window is chosen as the 60 days prior to the event window. The estimated abnormal return is:

$$(3.26) \quad AR_{i,\tau} = R_{i,\tau} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,\tau}),$$

where  $AR_{i,\tau}$  is the difference between the actual return and estimated return.  $\hat{\alpha}_i$  and  $\hat{\beta}_i$  are estimated using the ordinary least square method as follows:

$$(3.27) \quad \hat{\alpha}_i = \hat{\mu}_i - \hat{\beta}_i \hat{\mu}_m$$

$$(3.28) \quad \hat{\beta}_i = \frac{\sum_{\tau=t_0}^{t_1} (R_{i,\tau} - \hat{\mu}_i)}{\sum_{\tau=t_0}^{t_1} (R_{m,\tau} - \hat{\mu}_m)^2}$$

$$(3.29) \quad \hat{\sigma}_{\hat{\varepsilon}_i}^2 = \frac{1}{t_1 - 1} \sum_{\tau=t_0}^{t_1} (R_{i,\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m,\tau})^2.$$

---

<sup>24</sup>The FSIS recalls in 2007 is available from FSIS Recall Case Archive website: [http : //www.fsis.usda.gov/fsis\\_recalls/RecallCaseArchive2007/index.asp](http://www.fsis.usda.gov/fsis_recalls/RecallCaseArchive2007/index.asp). The FDA recalls in 2007 is published from its website: [http : //www.fda.gov/oc/po/firmrecalls/archive2007.html](http://www.fda.gov/oc/po/firmrecalls/archive2007.html).



The average abnormal return for  $N$  events during event period  $\tau$  is:

$$(3.30) \quad AAR_{\tau} = \frac{1}{N} \sum_{i=1}^N AR_{i,\tau}.$$

The cumulative average abnormal returns are calculated as the averaging over the event window,  $T_2$ :

$$(3.31) \quad CAAR_{t_1,t_2} = \sum_{\tau=t_1}^{t_2} AAR_{\tau}.$$

We tested the statistical significance of CAAR using the null hypothesis that the abnormal returns are significantly different from zero. The t-statistic is calculated as:

$$(3.32) \quad t_{CAAR_{t_1,t_2}} = \frac{CAAR_{t_1,t_2}}{\sqrt{CAAR_{t_1,t_2}}}.$$

Following MacKinlay's (1997) study, we estimated the parameters of the market model ( $\alpha$  and  $\beta$  in Equation 3.25) for each firm by regressing its actual returns on the returns of S & P 500 index during the same estimation period of 60 days prior to the event window. The estimated market model parameters,  $\hat{\alpha}$  and  $\hat{\beta}$ , are used to calculate abnormal returns. The stock portfolio is composed of 17 firms for 18 FDA food recalls and 5 firms for 7 USDA food recalls during 2007.<sup>25</sup> The cumulative average abnormal returns ( $CAAR$ ) for days  $\pm 22$  for FDA and USDA recalls are shown in Figure 3.2.

Figure 3.2 presents the average abnormal returns for the recall announcements on the event day, as well as for an event window of  $\pm 22$  days around the event day. Results show that, on average, announcements of food recall are associated with negative excess returns in the stock market. The  $CAAR$  for both FDA and USDA recall announcements demonstrate

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<sup>25</sup>We chose the recalls between January to November 2007 due to the availability of data. Only those firms that are publicly traded in the NYSE or NASDAQ are selected. The sample in our study consists of 18 out of 384 FDA recalls and 7 out of 54 USDA recalls during 2007. There are two reasons for the limit of our sample size: first, over 60% of the firms associated with food recalls are private firms; and second, about 40% of the recall announcements are general health and safety warnings and no specific company names are mentioned. For a complete list of the sample size and recall case description, see Tables A.3, A.4, A.5, and A.6. Our sample in FDA recalls also include four cases of nonfood recalls.

FIGURE 3.2

Cumulative Average Abnormal Returns for FDA  
and USDA Recalls ( $\pm 22$  Days)

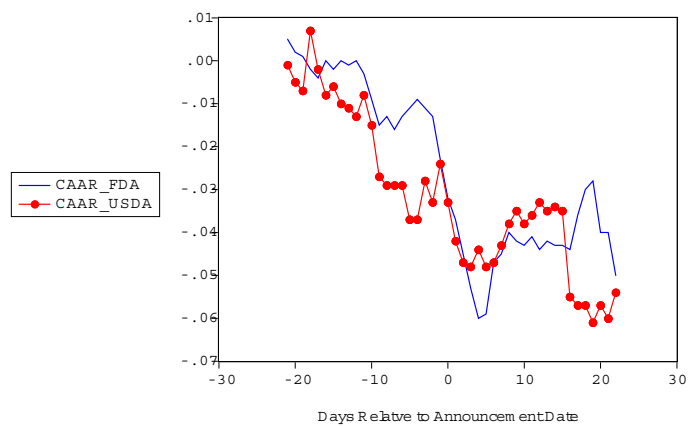
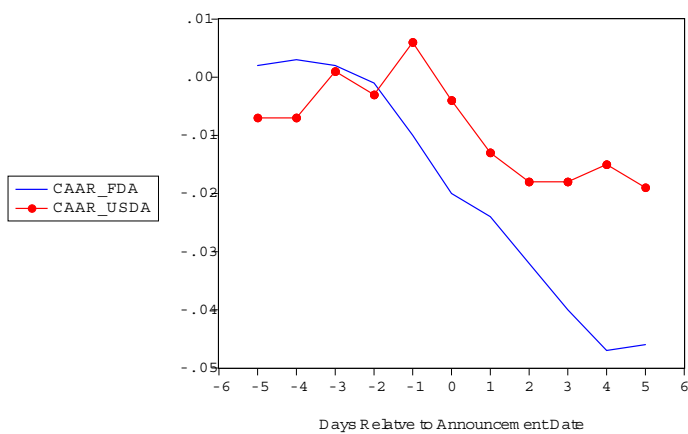


FIGURE 3.3

Cumulative Average Abnormal Returns for FDA  
and USDA Recalls ( $\pm 5$  Days)



a clear pattern of negative movement of stock returns. A return run-down is evident as early as day -10 for USDA recalls and return decreases almost 4% on the announcement date. The trends of *CAAR* for FDA depict a more informative picture of downturn movement prior to the events. Stock returns related to FDA recalls suffer from a loss of almost 6% one day before and one day after the recall announcement. Tables 3.15 and 3.16 present the average abnormal returns and cumulative average abnormal returns for FDA and USDA recalls over the study period of 2007. The fact that the stock return retreat starts one or two days prior to the recall announcement may serve as an indication of insider-trading activity. The recall information could have been available to investors through sources other than the government. For FDA recalls, the stock return reaches its lowest point two days after the announcement but bounces back quickly in the following 5 to 15 days for about 2%. The return movement after the announcement is less intuitive for USDA recalls. In general, investors experience significant losses  $\pm 2$  around the announcement day and returns remain flat from 10 to 15 days after the announcement.

However, the volatility of the *CAAR* in the tail part of Figure 3.2 signals additional information flow during that period of time. In other words, market news other than the food recall announcements begin to affect the stock market prices around 5 days after the event date. Thus, we shorten the event window to  $\pm 5$  days around the food recall announcement day, and these results are reported in Figure 3.3. The *CAAR* for FDA recalls flattens two days after the event while the figure of USDA recalls continues to decline after the announcement. Combining Figures 3.2 and 3.3, we conclude that food recall announcements have a negative impact on the return of the associated companies, but the negative effects die out in a short period of time (around 5 days).

### 3.5 Concluding Comments

The first part of this paper analyzes a new way of modeling intraday volatility and return. We modified the High-Frequency Multiplicative GARCH model and improved the model performance through the decomposition of the conditional variance into three parts that can be estimated and interpreted. The empirical results show that even after filter-

TABLE 3.15

Abnormal Returns of FDA Food Recalls

Event Day	AAR	CAAR
-5	0.002	0.002
-4	0.001	0.003
-3	-0.002	0.002
-2	-0.002	-0.001
-1	-0.010	-0.010
0	-0.009	-0.020
1	-0.004	-0.024
2	-0.008	-0.032
3	-0.008	-0.040
4	-0.007	-0.047
5	0.001	-0.046

TABLE 3.16

Abnormal Returns of USDA Food Recalls

Event Day	AAR	CAAR
-5	-0.007	-0.007
-4	0.000	-0.007
-3	0.009	0.001
-2	-0.005	-0.003
-1	0.009	0.006
0	-0.010	-0.004
1	-0.009	-0.013
2	-0.005	-0.018
3	0.000	-0.018
4	0.004	-0.015
5	-0.005	-0.019

ing the daily and diurnal volatility component, the intraday volatility remains persistent through the trading hours. We applied the model to a single stock SLE and three food sectors during March 2007. The second part of this paper is a study of the dynamics between intraday and overnight returns. Contrary to most of the research on overnight surprises, our research does not find a strong relation between intraday and overnight returns. We analyze both FDA and USDA recall cases. For FDA recalls, which include food, pet food, and farm animal feed, the top ten most actively traded companies are selected in each of the three food sectors. For USDA recalls, which include meat and poultry products, and eggs, two meat recall cases are selected during March 2007. We analyze the relation between intraday and overnight returns of the two associated companies. There are two possible explanations to this insignificant relation. The first is the fast dying-out effect of overnight news during the opening of the market. So most of the news impact has already been priced in during the trading hours and reflected in the intraday volatility. We assume that the overnight news is fully reflected in the opening price. Secondly, in our empirical study of the recall market, the majority of the news happens during the day as opposed to the close of the market. This is consistent with the high volatility during the trading hours in comparison with the off-trading hours. In the third part, we apply an event study approach to the FDA and USDA recalls during 2007. Research results show that stock returns start to decline around two days prior to the announcement of the recall, and the total loss to an investor invested in those associated stocks is about 4 to 6%. Stock returns remain flat for around 10 to 15 days with some degree of volatility, which is more evident in the USDA recall cases than the FDA recall cases. The negative impact of food recalls dies out around 5 days after the announcement.

## CHAPTER 4

## CONCLUSIONS

This dissertation has examined two different groups of objectives in the realm of macro and financial economics. Aggregate investment fluctuation and individual firms' interdependence behavior, intraday volatility, intraday and overnight returns, and stock markets' responses toward a food recall event are studied in two essays. The first essay of this dissertation presents a distributional test and an econometric model that investigates the amplification mechanism of aggregate investment fluctuation. We present empirical evidence that the fraction of firms that experience a large investment rate in the same region and industry is distributed exponentially. This finding puts a question on the modeling strategy that attributes the cause of aggregate investment fluctuations to a collection of unspecified exogenous shocks outside of the model, because such a collection of shocks will form a Gaussian noise to the aggregate investment. An alternative model of endogenous investment fluctuations is proposed to analyze the endogenous effects of firms' investment behavior. This econometrical model has a robust nature to generate the exponential distribution and separates individual firms' interdependence reaction from the exogenous effects of common shocks.

The second essay of this dissertation empirically tests and estimates a modified High-Frequency Multiplicative Components GARCH model using a sample of interday and intraday trading data from over 30 publicly traded food sector companies in the United States in 2007. The modified High-Frequency Multiplicative Components GARCH model breaks daily volatility into three parts: daily volatility, deterministic intraday volatility, and stochastic intraday volatility. An empirical application of this econometric model shows a significant level of persistence of stock market return intraday volatility. Based on a study of dynamics between intraday and overnight returns, this study concludes that there is little connection between the intraday and overnight returns. This is consistent with the

high volatility during the trading hours in comparison with the off-trading hours. In the third part, we apply an event study approach to the FDA and USDA recalls during 2007. Research results show that stock returns start to decline around two days prior to the announcement of the recall, and the total loss to an investor invested in those associated stocks is about 4 to 6%. Stock returns remain flat for around 10 to 15 days with some degree of volatility, which is more evident in the USDA recall cases than the FDA recall cases. The negative impact of food recalls dies out around 5 days after the announcement. By following an event analysis methodology, our study finds strong evidence that the food recall announcements have negative impacts on the asset returns of the associated publicly traded firms.

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APPENDIX

FIGURE A.1

Histogram of Firm's Investment Rates  $IPK(i, t)$  (Threshold = 30%)

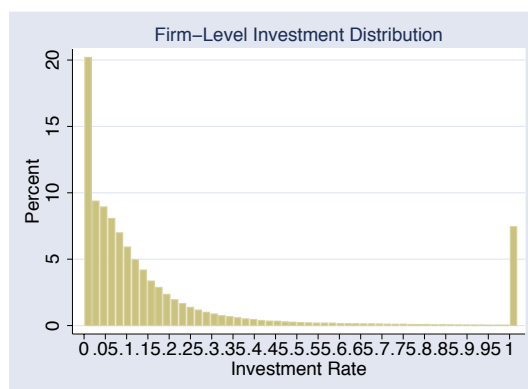


FIGURE A.2

Histogram of Firm's Investment Rates  $IPK(i, t)$  (Threshold = 10%)

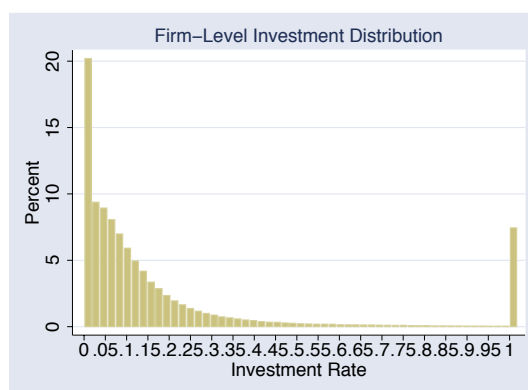


FIGURE A.3

Histogram of Firm's Investment Rates with  $IPK(i, t)$  from 1 to 50

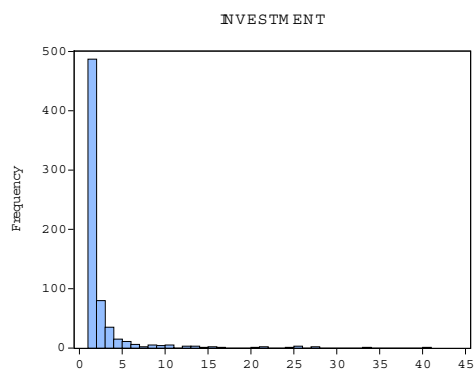


FIGURE A.4

Histogram of Firm's Investment Rates with  $IPK(i, t)$  from 1 to 100

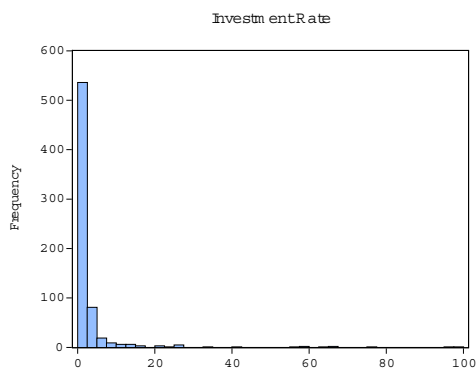


TABLE A.1

Estimation Results for Daily Volatility GARCH ( $p$  and  $q$ ) Model

	$\omega$	$\beta$	$\gamma$	AIC	Log Likelihood
p=0, q=1	.000 (.000)	$\beta_1 = -.124$ (.311)		-6.543	74.969
p=1, q=1	.000 (.000)	$\beta_1 = -.191$ (.238)	$\gamma_1 = 1.163^{**}$ (.254)	-6.708	77.788
p=1, q=2	.000 (.000)	$\beta_1 = -.055$ (.354) $\beta_2 = -.815$ (.768)	$\gamma_1 = -.034$ (.311)	-6.514	76.652
p=2, q=1	.000 (.000)	$\beta_1 = -.249$ (.287)	$\gamma_1 = .876$ (1.181) $\gamma_2 = -.364$ (1.146)	-6.629	77.291
p=2, q=2	.000 (.000)	$\beta_1 = -.267$ (.269) $\beta_2 = -.137$ (.402)	$\gamma_1 = .503$ (1.493) $\gamma_2 = .832$ (1.629)	-6.592	78.510

TABLE A.2

Estimation Results for Stochastic Intraday Volatility GARCH ( $p$  and  $q$ ) Model

	$\omega$	$\beta$	$\gamma$	AIC	Log-Likelihood
p=0, q=1	.779** (.003)	$\beta_1 = .187^{**}$ (.004)		2.772	-28975.3
p=1, q=1	.064** (.002)	$\beta_1 = .093^{**}$ (.002)	$\gamma_1 = .843^{**}$ (.004)	2.718	-28406.9
p=1, q=2	.040** (.002)	$\beta_1 = .141^{**}$ (.003) $\beta_2 = -.078^{**}$ (.002)	$\gamma_1 = .898^{**}$ (.003)	2.724	-28415.2
p=2, q=1	.079** (.003)	$\beta_1 = .117^{**}$ (.003)	$\gamma_1 = .448^{**}$ (.020) $\gamma_2 = .356^{**}$ (.018)	2.719	-28410.3
p=2, q=2	.015** (.000)	$\beta_1 = .136$ (.269) $\beta_2 = -.110^{**}$ (.003)	$\gamma_1 = 1.375$ (1.493) $\gamma_2 = -.415^{**}$ (.034)	2.720	-28420.7

TABLE A.3

## Sample Size of FDA Recalls

Month	Number of Recalls	Number of Recalls Associated with Publicly Traded Firms
January	16	0
February	31	0
March	58	7
April	46	0
May	37	1
June	27	1
July	24	2
August	34	1
September	28	1
October	25	4
November	24	1
December	34	0
Total	384	18

TABLE A.4

## Sample Size of USDA Recalls

Month	Number of Recalls	Number of Recalls Associated with Publicly Traded Firms
January	9	0
February	5	2
March	3	3
April	4	0
May	4	0
June	7	1
July	4	0
August	2	0
September	4	0
October	3	1
November	5	0
December	4	0
Total	54	7

TABLE A.5

## FDA Class I Recalls and Safety Alerts During 2007

Date	Description of the Recall
March 6	Bausch & Lomb Initiates Limited Voluntary Recall of Twelve Lots of ReNu MultiPlus Solutions Due to Potential for Shortened Shelf Life
March 9	BJ's Wholesale Club Issues Recall of "Berkley & Jensen" Full-Cut Pig Ears Dog Treats Because of Potential for Salmonella Contamination;
March 9	Safeway Recalls Bread in Parts of California and Nevada
March 16	Ben & Jerry's Issues Allergy Alert on Undeclared Wheat in Ben & Jerry's Country Peach Cobbler Ice Cream
March 16	Hill's Pet Nutrition Announces Voluntary Participation in Menu Foods's Nationwide U.S. and Canadian recall of Specific Canned Cat Foods
March 24	Menu Foods Initiates Market Withdrawal of Wet Pet Food to Ensure Consumer Protection
March 30	Del Monte Pet Products Voluntarily Withdraws Specific Product Codes of Pet Treats and Wet Dog Food Products
May 25	Abbott Announces Voluntary Nationwide Recall of Similac Special Care Premature Infant Formula with Iron
June 5	Class I Recall: Alcon Refractive Horizons LADAR6000 Excimer Laser System
July 13	Gerber Announces Nationwide Voluntary Recall of Gerber ORGANIC Rice Due to a Potential Choking Hazard
July 31	Whole Foods Market Issues Allergy Alert on Undeclared Nuts in 365 Organic Everyday Value Swiss Dark Chocolate Bars
August 31	Urgent: Abbott Notifies Users of Kroger Blood Glucose Meters to Check Display Screens
September 17	Dole Announces Voluntary Recall of 'Dole Hearts Delight' Packaged Salads
October 3	Kraft Foods Recalls Baker's Premium White Chocolate Baking Squares Because of Possible Health Risk
October 4	Campbell Voluntarily Recalls Chunky Baked Potato With Cheddar & Bacon Bits
October 5	Winn-Dixie Stores, Inc. Issues Allergy Alert on Mislabeled Prestige Chocolate Ice Cream
October 15	Statement on Medtronic's Voluntary Market Suspension of Their Sprint Fidelis Defibrillator Leads
November 16	Updated Recall Information: Thoratec Corporation Implantable Ventricular Assist Devices (IVAD)

TABLE A.6

## USDA Recalls Archive During 2007

Date	Description of the Recall
February 12	ConAgra Foods, Inc., a Milton, Pa., establishment, is voluntarily recalling approximately 402,623 pounds of pasta and meatball meals due to possible underprocessing.
February 3	Morgan Foods, an Austin, Ind., firm, is voluntarily recalling approximately 6,317 pounds of chicken noodle soup due to the presence of undeclared allergens (milk, soy).
March 2	Tyson Fresh Meats, a Wallula, Wash., firm, is voluntarily recalling approximately 16,743 pounds of ground beef that may be contaminated with E. coli O157:H7.
March 9	Hempler Foods Group, a Ferndale, Wash., firm, is voluntarily recalling approximately 5,084 pounds of summer sausage due to the presence of an undeclared allergen, hydrolyzed sodium caseinate (milk protein).
March 27	Kraft Foods Global, Inc., a Kirksville, Mo., establishment, is voluntarily recalling approximately 1,800 pounds of bacon due to insufficient cooling during processing.
June 8	Tyson Fresh Meats, Inc., a Sherman, Texas, establishment, is voluntarily recalling approximately 40,440 pounds of ground beef products due to possible contamination with E. coli O157:H7.
October 11	ConAgra Foods, a Marshall, Mo., firm, is voluntarily recalling an undetermined amount of all varieties of frozen pot pie products in commerce that may be linked to an outbreak of salmonellosis.

## VITA

## EDUCATION:

BS in Finance, Southwestern University of Finance and Economics, Chengdu, China, July 2000. Thesis: A Study of the Overseas Listings of Chinese Firms. GPA: 3.6

Ph.D. in Economics, Utah State University, Logan, Utah (expected December 2008).  
Dissertation: Essays on Investment Analysis and Market Volatility Analysis. GPA: 4.0

## EXPERIENCE:

Research Assistant, Department of Economics, Utah State University, Logan, UT. (04-08)

Developed a distributional test and a general equilibrium model to test the endogenous investment fluctuation. Presented paper “Distributional Test for Endogenous Effects” at Weber State University and Utah State University, October 2007. Developed a policy decision model and applied it to the strategies of improving water quality in Bear River, UT, through permit trading and cost sharing. Coauthored paper “Initiating the Water Quality Trading Process: The Impact of Agency Subsidization,” November 2005.

Instructor, Department of Economics, Utah State University, Logan, UT. (07-08)  
ECON 3400 (International Economics for Business) and ECON 5010 (Intermediate Microeconomics)

Undergraduate Research Assistant, School of Business and Administration, Southwestern University of Finance and Economics Chengdu, China.(03-04)

## PAPERS AND PROCEEDINGS:

“Distributional Test for Endogenous Effects: Case of Binary Investment”, paper presented at Utah State University and Weber State University, October 2007



“Initiating the Water Quality Trading Process: The Impact of Agency Subsidization”, 2005, working paper, Department of Economics, Utah State University, and paper presented to the East West Center, University of Hawaii, November 22, 2005

“Targeting Federal Funds Rate”, paper presented at Federal Open Markets Committee and Monetary Policy Simulation conducted by the Federal Reserve Bank of San Francisco, Utah State University, October 2004

COMPUTER SKILLS: STATA, SAS, Eviews, and LaTeX

AWARDS AND HONORS:

First Place Winner the Tenth Intermountain Paper and Poster Symposium, Utah State University, Logan, UT. (4/07)

Undergraduate Scholarship and Dean’s List, Southwestern University of Finance and Economics, Chengdu, China. (00-04)