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Essays on finance, investment, and money

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Essays on finance, investment, and money

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this dissertation. The Graduate College will ensure this dissertation is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

For Layla

TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

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ABSTRACT

Three chapters in this dissertation revolve around the areas of empirical corporate finance and behavioral finance, with particular focuses on firms' R&D financing, the manager side of behavioral finance, and the effect of network formations on media of exchange.

Chapter 2 examines the effects of the financial side of the firm on labor. These effects have not been studied extensively. Using the system Generalized Method of Moments, fixed effects, and IV models, this chapter shows that balance sheet liquidity (cash holdings) can help maintain stable employment in response to demand shocks.

Chapter 3 implements human-subject experiments. It shows how contrast effects from psychology studies influence investment and financing decisions. This chapter illustrates that individuals exposed to a positive stimulus amplify risk-seeking in investment decisions compared to individuals exposed to a negative stimulus. However, exposure to positive or negative stimuli does not affect financing decisions. It is likely that financing decisions require a high cognitive load, so they are less affected by emotions.

Chapter 4 examines how different types of trade networks influence the emergence of one or more types of money. Many new types of monetary networks have emerged such as cryptocurrency networks. However, the underlying reason for the emergence of new money types is not well understood. Using an agent-based computer model, this chapter shows that the emergence of multiple goods as media of exchange depends on the network structure governing trade between agents.

CHAPTER 1. INTRODUCTION

My dissertation is motivated from emerging non-trivial issues with respect to finance, investment, and money. It examines the previous three issues using empirical, experimental, and theoretical approaches, respectively.

The first issue, presented in Chapter 2, is that the financial side matters to the performance of a firm. The effects of the financial side of the firm on labor have not been extensively studied. Giroud and Mueller (2017) show that firms with high leverage reduce employment levels more than firms with low leverage in response to consumer demand shocks. Ultimately, they show firms' balance sheets can affect the employment levels of firms. Chapter 2 extends the idea of Giroud and Mueller (2017) by showing that firms with high balance sheet liquidity (cash holdings) can buffer more labor declines in response to consumer demand shocks.

The second issue, presented in Chapter 3, is that the emotions of individuals can influence their decision making. Psychology studies illustrate emotions can affect agents to form expectation. Simonsohn and Lowenstein (2006) use contrast effects from psychology studies to explain why people from cities rent more expensive apartments than people from countryside, even after taking account of wealth and taste. Inspired by Simonsohn and Lowenstein's paper (2006), Chapter 3 shows how contrast effects influence investment and financing decisions. Using an experiment developed by Harbaugh et al. (2009), this chapter finds that a positive stimulus makes people to become more risk-seeking in investment decisions.

The third issue, presented in Chapter 4, is that a new type of network has emerged regarding money, such as a cryptocurrency network. It is still unknown what types of underlying networks are money networks. Studying the emergence of money as a medium of exchange is not new. However, Chapter 4 examines how different types of networks influence the emergence of money, which have not been significantly studied. Combining the Kiyotaki-Wright model (1989) with Wilhite's four different trade networks (2001), this chapter shows that trade networks can make agents to adopt speculative strategies, which lead to the emergence of multiple media of exchange.

CHAPTER 2. FINANCING R&D, FINANCIAL CONSTAINTS, AND EMPLOYMENT

This study examines the speed of labor adjustment in high-tech and non-high-tech firms and the effect of balance sheet liquidity (cash holdings) on employment changes in response to consumer demand shocks. It offers robust evidence that firms in the high-tech sector, which account for most R&D and are thus financially constrained, adjust employment toward the target employment slowly. The finding supports that adjustment costs for labor in high-tech firms are high. This study also documents that firms with more cash holdings show fewer employment changes in response to consumer demand shocks. These effects are amplified within high-tech firms. The results suggest that cash holdings may help other financially constrained firms such as small firms to maintain stable employment in response to consumer demand shocks.

Introduction

Firms with high R&D consider human capital as one of their greatest assets because these workers have critical knowledge that embodies firm intellectual property. High R&D firms value the information and skills their workers possess more than firms with low R&D. Hence, it would result in critical damages to high R&D firm values if they cut human capital (Hall, 2002). Firms in the high-tech sector invest the most in R&D across sectors (Brown et al., 2017). Thus, it is critical for high-tech firms to achieve the desired employment levels and maintain stable employment levels for high-tech firms in response to consumer demand shocks.

There is a large body of empirical literature on labor adjustment and employment changes in response to exogenous shocks for each firm (Erashin and Irani, 2015; Giroud and Mueller, 2017; Kleiner, 2015). Unlike previous studies that focus on the role of household and financial intermediary balance sheets (Guerrieri and Lorenzoni, 2017; Midrigan and Philippon 2016; Moreira and Savov, 2017), Giroud and Mueller (2017) argue firms' balance sheets, like corporate structures, take a critical role in the transmission of consumer demand shocks. This paper provides a comprehensive study to compare the speed of labor adjustment in high-tech and non-high-tech firms, and also shows how balance sheet liquidity (cash holdings) affects employment changes in response to consumer demand shocks in financially constrained and unconstrained firms. It shows that cash holdings are critical to maintain stable employment for financially constrained firms, particularly for high-tech and small firms. This contributes to the literature by showing that the financial side of a firm matters to labor.

The dynamics of labor adjustment have been extensively studied (Caballero and Engel, 1993; Caballero, Engel, and Haltiwanger 1997). Caballero, Engel, and Haltiwanger (1997) find that the gap between the actual and desired (target) employment levels influences employment changes. Caballero and Engel (1993), on the other hand, use a structural model to find the dynamics of labor adjustment. In this paper, the model developed by Caballero, Engel, and Haltiwanger (1997) is estimated by using a system Generalized Method of Moments (GMM) estimator. This estimator can settle potentially endogenous regressors and firm fixed effects (Arellano and Bover, 1995; Blundell and Bond, 1998). Using both the dynamic panel and cross-section analyses, this paper finds that firms with more R&D as a percentage of total assets show a low speed of labor adjustment. In other words, high R&D firms adjust employment toward their target employment levels more slowly because the speed of labor adjustment is inversely related to adjustment costs. The adjustment costs for labor are high for high-tech firms, so the results are consistent with previous studies.

To compare the speed of labor adjustment between high R&D firms and low R&D firms, the causal link between R&D and employment needs further examination. This link is not clearly established due to the possibility of confounding factors that are not included in the analysis or due to the likely endogeneity of R&D. As examples, young firms are more likely to invest in R&D, and young firms have faster growth rates. Therefore, the link may be due to the age of the firm. A second possibility is that firms with growing sales volumes may expand their investments in employment and R&D, and so the missing causal factor is the growth in firm demand. Or, it may be that expansion in R&D comes at the expense of other inputs including employment. These are just three of many possible reasons that the correlation between R&D and employment may not be causal. Thus, this paper uses an alternative approach suggested by the literature to divide the sample into a high-tech sector and a non-high-tech sector, and identifies the impact of R&D on firms' labor demand.

The speed of adjustment has been studied widely in a financial context. Faulkender et al. (2012) find that cash flow realization can reduce leverage adjustment costs. Eventually, firms with high cash flows have a faster speed of adjustment towards leverage targets. Similar properties are observable in firms with more dividend smoothing. In particular, cash cows and firms with lower volatility in earnings and returns exhibit more dividend smoothing (Leary and Michaely, 2011). In empirical specifications, this paper follows Faulkender et al.'s (2002) approach to measure the speed of labor adjustment using the system GMM approach.

Several recent papers have investigated the effect of firms' balance sheets on employment. Giroud and Muller (2017) find firms' balance sheets play a critical role in employment changes during crises. They show that firms with high leverage suffer a substantial decline in employment when they face housing price shocks, which are used as proxies for consumer demand shocks (see Mian, Rao, and Sufi, 2013). Ersahin and Irani (2015) note that shocks to real estate, which lead to change in collateral values, influence employment. Kleiner (2015) explains the decline of employment in the Great Recession by the decrease in housing values.

Other studies relate the financial side of a firm to employment. In a discussion of finance, Berger (2015) finds that access to finance matters in employment. She offers evidence that an increase in local finance leads to employment growth. In general, channels for external financing tighten when there are supply shocks. Then, cash reserves play a critical role during financial crises (Duchin et al., 2010). Duchin et al., (2010) also find firms with low cash reserves reduce investments more than the others.

This study documents how liquidity management (holding more cash) can buffer employment changes in response to consumer demand shocks. Using Hall's identification strategy (2002), which explains that the financial side of a firm matters for R&D expense, this paper argues that the financial side of a firm influences the firm-level employment since salaries of employees account for most R&D expense. The paper shows that cash holdings play a critical role in maintaining stable employment levels in response to demand shocks. These effects are amplified within financially constrained firms like high-tech and small firms.

Background and Empirical Predictions

Financing R&D: Cash, Leverage, External Equity

According to the Modigliani-Miller theorem (1958), the capital structure of a firm cannot influence investment decisions since it assumes perfect capital markets with no financial frictions. This assumption leads to the same cost of funds between internal financing and external financing. However, in real-world situations, financial frictions such as information and transaction costs lead to different costs of funds across sources of financing. Hall (2002) illustrates the identification of investments by showing how different costs of funds can change investments in Figure 2.1. The cost of funds will increase after internal funds are exhausted as shown in points A and B in Figure 2.1.

The downward-sloping curve in Figure 2.1 represents the demand for R&D investment funds; the upward-sloping curves represent the supply of R&D investment funds. If a firm has enough internal funds to finance investments, the firm is financially unconstrained as shown in point C. However, if firms need to use external funds, investments decrease from point C to point D. A positive shock in internal funds, such as an increase in cash holdings, can shift investments from point D to point C.

On the other hand, the cost of funds varies between investments in fixed (tangible) assets and R&D (intangible) assets. The costs for financing R&D investments are likely to be more expensive, mainly due to high information costs (Brown et al., 2009; Brown et al., 2012; Hall, 2002). The pecking order theory (Myers and Majluf, 1984) argues that internal financing costs the least among sources of funds. Then, external financing with debt is the next least costly source because banks prefer to finance for physical assets. External financing with issuing equity is the most costly because of high transaction and information costs caused by information asymmetries. R&D investments are seldom financed by debt (Brown et al., 2009; Brown et al., 2012). For instance, some firms may not be able to borrow money from banks at the same cost of funds due to credit rationing (Stiglitz, 1988). This limitation in sources of funds makes firms with high R&D more financially constrained (Brown et al., 2009; Brown et al., 2012).

Labor Adjustment and Employment Changes

R&D is mainly composed of salaries for high-skilled workers. These workers produce intangible assets such as patents and business methodologies. In other words, R&D could be embodied in workers, and the firm risks losing intellectual property or development potential if it loses its researchers. Hiring and training costs are higher for these workers; therefore, firms with high R&D consider workers as one of their greatest assets. It would be more of a loss if workers left a high R&D firm compared to a firm with low R&D. Thus, firms with high R&D have high adjustment costs for labor, and this leads to:

Prediction 1: It is anticipated that high-tech firms adjust employment toward their target employment levels more slowly due to high adjustment costs for labor.

This paper applies a framework developed by Caballero, Engel, and Haltiwanger (1997). They argue that employment changes depend on the difference between the desired and actual employment as shown in Equation (1). $Employee_{i,t}$ represents the level of employment at time *t* for firm *i*.

$$Ln(Employee)_{i,t} - Ln(Employee)_{i,t-1} = \gamma(Employee\ deviation)_{i,t} \quad (1)$$

$$Employee\ deviation_{i,t} \equiv Ln(Employee)^{*}_{i,t} - Ln(Employee)_{i,t-1} \quad (2)$$

$Employee^{*}_{i,t}$ is the desired level of employment. Then, $Employee_{i,t-1}$ is the level of employment before the adjustment at time *t*. The speed of labor adjustment toward the target levels is not extensively studied across sectors. Using an approach developed by Caballero, Engel, and Haltiwanger (1997), the speed of labor adjustment in the high-tech sector is estimated in this study.

Giroud and Mueller (2017) argue firms' balance sheets are critical in employment changes during crises. In particular, high leverage leads to more reduction in employment in response to demand shocks (Giroud and Mueller, 2017). Likewise, the depreciation in housing values, which decreases collateral values, affects change in the employment levels of firms. However, the effect of cash holdings on employment levels is not well documented.

Brown and Petersen (2011) show that cash holdings are critical in smoothing R&D investments. Since the biggest share of R&D is salaries of workers, employment levels should be affected by cash holdings. This discussion leads to:

Prediction 2: It is anticipated that more cash holdings should help buffer employment levels in response to demand shocks. This prediction should be amplified within the high-tech sector as well as other financially constrained firms since cash holdings are more critical for these firms.

Data and Sample Characteristics

Sample Construction

The data to construct the sample used in this study is from Compustat and Zillow. Compustat database provides detailed financial information of publicly traded firms in the United States. This study focuses on publicly traded firms because they account for the most R&D spending in the U.S. It is hard to finance R&D investments if the firm stays private (Brown and Petersen, 2010). The firm-level data from 1997 to 2014, which will be used to create the main variables, are collected excluding the following firms: finance (SIC 60-69), public utilities (SIC 49), and public administration (SIC 90-99). Then, firms with negative assets, negative sales, and less than four employees are dropped from the data used to construct the sample. Also, the sample excludes firms that do not report at least one string of five consecutive employee observations. Housing price is measured by median home values per square foot available at the zip code level from Zillow. This data is merged in the sample using the location of company headquarters and year. For instance, the headquarters of AAR corporation was located at 60191 in 1997, and the median home value per square foot at this zip code was $142 in 2017 according to Zillow. This results in the acquisition of unbalanced panel data with 32,652 observations. All variables are winsorized at 1% level to account for outliers. Table 2.1 shows descriptions of the main variables.

Industries and Descriptive Statistics

The following industries are in the high-tech sector (Brown et al., 2009; Brown et al., 2017): drugs (SIC 283), computer and office equipment (SIC 357), communications equipment (SIC 366), electronic components and accessories (SIC 367), laboratory instruments (SIC 382), medical instruments (SIC 384), and computer related services (SIC 737). These high technology industries, according to the U.S. Department of Commerce, are characterized by high engineering and scientific capabilities and technological development. As shown in Figure 2.2, these seven industries take account of 72% of the total R&D in the U.S. during the sample period. The rest of the industries are considered as the non-high-tech sector for the following analysis. In the sample, the high-tech sector comprises 10,173 observations and the non-high-tech sector consists of 22,479 observations.

Table 2.2 shows the mean and median for main variables across sectors. As noted above, the mean of R&D scaled by total assets is significantly greater in the high-tech sector (Hall 2002; Brown et al., 2009; Brown et al., 2012). Also, both the mean and median of cash holdings scaled by total assets are greater for firms in the high-tech sector. It shows that firms with high R&D keep larger cash holdings than firms with low R&D. Last, this table shows that leverage is low in the high-tech sector. It can be explained by the limitation of financing through debt. High-tech firms, on average, have a higher Tobin's Q, which can imply a high growth potential. On the other hand, non-high-tech firms show large absolute values for firm size, age, Size-Age index, and Whited-Wu index. These all imply that high-tech firms are more financially constrained.

Empirical Specification and Results

Speed of Labor Adjustment

A firm's speed of labor adjustment toward targets is estimated using the gap approach developed by Caballero, Engel, and Haltiwanger (1997). This study argues that a firm's speed of labor adjustment varies by spending on R&D. However, there is an issue of the endogeneity of R&D so this study uses the Standard Industrial Classification in Compustat to construct high-tech sector and non-high-tech sector instruments. $Employee_{i,t}$ is the number of employees of the firm *i* at time *t*. In Equation (1), γ represents the speed of labor adjustment toward the target employment level. In other words, the firm fills γ percent of the difference between the target employment and the lagged employment every discrete time period.

In Equation (2), the desired (target) employment level, $Employment_{i,t}^{*}$, is a theoretical construct (Caballero, Engel, and Haltiwanger, 1997). This study uses a model of labor demand developed by Berman, Bound, and Griliches (1993) to model the target employment level. Berman, Bound, and Griliches (1993) assume that the variable cost function is in a transcendental logarithmic form:

$$\begin{aligned}\ln(CV) = {} & \alpha_0 + \alpha_Y \ln(Y) + \sum_i \alpha_i \ln(W_i) + \beta \ln(K) + 0.5\gamma_{YY}\ln(Y)^2 \\ & + 0.5\sum_i\sum_j \gamma_{ij}\ln(W_i)\ln(W_j) + 0.5\delta\ln(K)^2 + \sum_i \rho_{Y_i}\ln(Y)\ln(W_i) \\ & + \sum_i \rho_i \ln(W_i)\ln(K) + \pi\ln(Y)\ln(K) + \phi_t t + 0.5\phi_{tt}t^2 + \phi_{tY}t\ln(Y) \\ & + \sum_i \phi_{tw_i} t\ln(W_i) + \phi_{tK} t\ln(W_i K)\end{aligned}$$

where Y indicates value added; K indicates capital; W_i and W_j indicate wages for *i* and *j* types of workers, respectively; t indicates a technological change; and CV indicates variable costs. Labor inputs (x_i) are variable. Their necessary assumptions (Berman, Bound, and Briliches, 1993) also include that there are constant returns to scale, and firms choose inputs to minimize costs. Using the envelope theorem, we know that $\frac{\partial CV^*}{\partial W_i} = x_i^*$, where x_i^* is the labor input of the *i* type of workers. We have $\frac{\partial \ln (CV^*)}{\partial \ln (W_{i)}} = \frac{\partial CV^*}{\partial W_i}\frac{W_i}{CV} = x_i^* \frac{W_i}{CV} = S_i^*$, where S_i^* is the share of wages for *i* type of workers in total wages. Then, we obtain $S_i^* = \alpha_i + \rho_{Y_i} \ln(Y) + \sum_j \gamma_{ij} \ln(W_j) + \rho_i \ln(K) + \phi_{tw_i} t$. This solution yields that labor inputs are influenced by capital. Inspired by Berman, Bound, and Griliches (1993), the target employment level comes from firms constrained in choosing capital levels.

In Equation (3), $X_{i,t-1}$ is a vector that includes firm characteristics for modeling the target employment level such as capital levels, Tobin's Q ratio, and financial variables. A higher Tobin's Q ratio is a signal of future growth of the company, which can lead to an increase in employment levels. This measure can be viewed as exogenous in the short run. Lagged *X* is used because firms do not respond immediately to decide target employment levels.

$$Employee_{i,t}^* = \beta X_{i,t-1} \qquad (3)$$

$$Ln(Employee)_{i,t} = \gamma\beta Ln(X)_{i,t-1} + (1-\gamma) Ln(Employee)_{i,t-1} + \epsilon_{i,t} \qquad (4)$$

As mentioned above in the "Financing R&D" section, the financial variables in $X_{i,t-1}$ include cash flows, stock issues, and debt issues. In Equation (4), the speed of labor adjustment (γ) is estimated using the system Generalized Method of Moments (GMM) estimator, which is introduced by Arellano and Bover (1995) and Blundell and Bond

(1998). Both Tobin's Q ratio and financial variables are potentially endogenous, so the system GMM approach uses lagged levels and lagged differences as instruments for regressions in differences and levels, respectively. This method solves problems of endogenous regressors and firm fixed effects. Because lagged levels of t-3 to t-4 are not appropriate in this case (see below), this study employs lagged levels of t-5 to t-6 as instruments for regressions in differences and lagged differences of t-4 as instruments for regressions in levels.

To verify instruments and specifications, the following tests are reported: a Hansen J-test, a difference-in-Hansen test, and an m2 test. The Hansen J-test addresses the validity of the over-identifying restrictions and a difference-in-Hansen test addresses the validity of the additional instruments in the levels equation. The m2 test addresses second-order autocorrelation for the first differenced residuals. These tests can show whether instruments and specifications have any problems. Using lagged levels of t-3 to t-4 as instruments for regressions in differences does not pass these tests.

Table 2.3 shows that the estimate of the speed of labor adjustment using the System GMM lies near the range between the other two estimates obtained from OLS and fixed effect models. The System GMM estimator is superior among the other estimators because it takes account of dynamic panel bias and fixed effects (Roodman, 2006). Using the System GMM as a base model, Table 2.3 shows that the speed of labor adjustment for high-tech firms and non-high-tech firms are 0.3% and 0.7%, respectively. The firms in the high-tech sector adjust employment level toward the target employment level slower than the non-high-tech sector. Although the difference in the speed of adjustment is modest, this is consistent with high adjustment costs for labor in the high-tech sector.

Change in Employment and Demand Shocks

This study uses a fixed effect model to find the effect of cash holdings on the change in employment levels in response to demand shocks. Equation (5) shows empirical specifications:

$$\Delta Ln(Employee)_{i,t} = \beta_1 Cash_{i,t-1} + \beta_2 \Delta Ln(Sale)_{i,t-1} * Cash_{i,t-1} + \beta_3 Leverage_{i,t-1} + \beta_4 \Delta Ln(Sale)_{i,t-1} * Leverage_{i,t-1} + \beta_5 \Delta Ln(Sale)_{i,t-1} + \beta_6 Tobin's\ Q_{i,t-1} + \delta_i + \theta_t + \epsilon_{i,t} \qquad (5)$$

Table 2.4 shows that cash holdings help to increase employment levels (in logs) since β_1 is positive. On top of that, β_2 is a negative value which supports that cash holdings decrease the sensitivity of the change in employment levels in response to demand shocks. For instance, Table 2.4 shows that if firms decrease sales by 10%, one unit of cash holdings can buffer a decrease in labor by 0.4%. Table 2.5 and Table 2.6 show that the absolute magnitude of the coefficient on $\Delta Ln(Sale)_{i,t-1} * Cash_{i,t-1}$ is greater for the high-tech sector than the non-high-tech sector. We reject the null hypothesis that these coefficients are statistically indistinguishable between the high-tech sector and the non-high-tech sector (p-value: 0.008). However, the coefficient on $Leverage_{i,t-1}$ is not statistically significant. Decomposing leverage to short-term and long-term leverages also yields the same results. This shows that cash holdings are critical in maintaining stable employment levels in response to demand shocks, especially in the high-tech sector. On the other hand, the coefficient on $\Delta Ln(Sale)_{i,t-1}$ is lower for the high-tech sector than for the non-high tech sector. It shows that high-tech firms try to buffer labor declines more in response to consumer demand shocks than non-high-tech firms.

This paper also uses a modification of empirical specifications developed by Giroud and Mueller (2017) to find how cash holdings influence the change in employment levels in response to demand shocks as shown in Equation (6). For this analysis, percentage changes in firm-level sales between 2006 and 2009 are used as demand shocks. However, due to the issue of endogeneity, percentage changes in house price at the zip code level between 2006 and 2009 are employed as instrumental variables for the sale percentage changes. Table 2.7 shows the result of the IV regression analysis.

$$\Delta Ln(Employee)_{i,2006-2009} = \beta_1 Cash_{i,2006} + \beta_2 \Delta Ln(Sale)_{i,2006-2009} * Cash_{i,2006} + \Delta Ln(Sale)_{i,2006-2009} + \epsilon_{i,t} \qquad (6)$$

The coefficients for the interaction term between $Cash_{i,2006}$ and $\Delta Ln(Sale)_{i,2006-2009}$ are negative. In other words, it is evident that cash holdings can help buffer labor declines, especially in response to large negative shocks where housing prices decrease by more than 10% on average. When there is a large negative shock, one unit of cash holdings can buffer labor declines by 1% in the event of a 1% decrease in sales. It is evident that cash holdings are critical for firms to buffer labor declines in response to demand shocks.

Financially Constrained and Unconstrained Firms

Cross-sectional Analysis: The Speed of Labor Adjustment

A cross-sectional analysis is used here to find the characteristics of firms that adjust employment levels quickly. This approach can help show what other firm characteristics aside from R&D influence the speed of labor adjustment. Inspired by Leary and Michaely (2011), the median employment level during the sample period is used for the target employment level, $Employee_{i,target}$, for each firm i.

$$\Delta Ln(Employee)_{i,t} = \gamma(Employee\ deviation_{i,t}) + \epsilon_{i,t} \qquad (7)$$

$$Employee\ deviation_{i,t} = \frac{Ln(Employee)_{i,target}}{Ln(Sale)_{i,target}} * Ln(Sale)_{i,t} - Ln(Employee)_{i,t-1}$$

(8)

Then, γ is estimated using Equation (7). Firms in the highest quartile adjust employment levels most quickly. Table 2.8 suggests that other proxies for financial constraints including size, age, Size-Age index and Whiter-Wu index do not relate to the speed of adjustment. In fact, Table 2.8 shows no significant patterns in firms' characteristics of the speed of adjustment, except R&D. Firms with more R&D adjust slowly toward the target employment level. These results closely follow the results in the "Speed of Labor Adjustment" section.

Financial Constraints and Changes in Employment

This study also divides the sample into financially constrained firms and unconstrained firms using firm size. Firms are defined as small (or large) if the asset size of the firm is below (or above) the median asset size of the sample. These firms are identified as financially constrained firms by the literature. By splitting samples, Equation (5) is estimated in Table 2.9 using the fixed effect model. Table 2.9 shows that the coefficient on $\Delta Ln(Sale)_{i,t-1}$ is lower for small firms. In other words, labor declines are less affected by consumer demand shocks in financially constrained firms as in the case of high-tech firms. Cash holdings seem to play a role in buffering labor for firms, particularly small firms. Since the coefficient on $\Delta Ln(Sale)_{i,t-1} * Cash_{i,t-1}$ is a negative value, cash holdings decrease the sensitivity of change in employment in response to housing price shocks for both small firms and large firms. The results are similar to those in the "Change in Employment and Demand Shocks" section. The absolute magnitude of the coefficient on $\Delta Ln(Sale)_{i,t-1} * Cash_{i,t-1}$ is greater for small firms than large firms. We can reject the null hypothesis that these coefficients are statistically indistinguishable at a significance level of 0.10 (p-value 0.094). The high absolute magnitude of β_2 indicates that cash holdings play a more critical role in financially constrained firms like high-tech and small firms.

Summary and Implications

Firms in the high-tech sector make up the most R&D spending in the U.S. Thus, they are more financially constrained due to the higher cost of funds mainly caused by information asymmetries. Internal financing and external equity are the main sources of funds for R&D. Since R&D is comprised mainly of the salaries of workers, employment levels are anticipated to be influenced by internal financing and external equity.

The empirical results in this study support these empirical predictions. Cash holdings of high-tech firms and other financially constrained firms help the firms to buffer employment levels in response to demand shocks such as sales shocks and housing price shocks. Additionally, the adjustment cost for labor in the high-tech sector is high. Confirming this prediction, the empirical results show that firms in the high-tech sector tend to adjust employment levels toward employment targets more slowly.

This study also shows cash holdings are necessary to maintain stable employment levels in response to demand shocks. These effects are amplified even further in the high-tech sector and financially constrained firms. Firms, particularly high-tech firms and financially constrained firms, should therefore possess adequate cash holdings in order to maintain stable employment levels in response to demand shocks.

To summarize, firms in the high-tech sector adjust employment levels toward employment targets more slowly, and financially constrained firms with more cash holdings are more likely to maintain stable employment levels in response to consumer demand shocks.Giroud and Mueller (2017) argue that employment policies should directly target firms, unlike previous studies that focus on indebted households (Guerrieri and Lorenzoni, 2017; Midrigan and Philippon 2016). They provide evidence that significant job losses in the Great Recession were mainly due to weak firm balance sheets in response to consumer demand shocks. Firms with high leverage experience more employment losses than firms with low leverage (Giroud and Mueller, 2017).

This paper strengthens their arguments for the importance of firm balance sheets by providing empirical evidence about the effect of cash holdings in different types of firms in response to consumer demand shocks. In Germany, short-time work programs encourage firms to reduce hours of employees instead of laying them off in response to consumer demand shocks. These programs reimburse firms to provide additional income to employees with reduced hours. Firms in Germany are subsidized to a great degree and these programs are successful in maintaining stable employment levels (Krugman, 2009).

Employment policies on targeting firms are critical, but the policies should vary across sectors. As shown in short-time work programs in Germany, it would be useful to provide subsidies to firms directly. This paper suggests that a subsidy in the form of cash holdings may even be better, which especially helps financially constrained firms to maintain stable employment levels in response to consumer demand shocks.

Figures and Tables

Table 2.1 Description of the Variables Used in This Study

Variable	Source	Description
Age_t	Compustat	Natural log of the difference between the fiscal year (FYEAR) and the first year that the company appeared in Compustat
$Size_t$	Compustat	Natural log of the book value of total assets (AT) in period t using the year 2012 dollar values
$Cash_t$	Compustat	Cash and short-term investments (CHE) in period t, scaled by the book value of total assets (AT) in period t
$Capital_t$	Compustat	Gross book value of property, plant, and equipment (PPEGT) in period t, scaled by the book value of total assets (AT) in period t
$CashFlow_t$	Compustat	Gross cash flow in period t, scaled by the book value of total assets (AT) in period t, where gross cash flow is the sum of income before extraordinary items (IB) and research and development expense (XRD) and depreciation and amortization (DP)
$StockIssues_t$	Compustat	Net cash inflow from stock issues in period t, scaled by the book value of total assets (AT) in period t, where cash inflow from stock issues is the sale of common and preferred stock (SSTK) plus the purchase of common and preferred stock (PRSTKC)
$DebtIssues_t$	Compustat	Net cash inflow from debt issues in period t, scaled by the book value of total assets (AT) in period t, where net cash inflow from debt issues is long-term debt issued (DLTIS) minus long-term debt reduction (DLTR)
$Leverage_t$	Compustat	Total debt in period t, scaled by the book value of total assets (AT) in period t, where total debt is equal to total long-term debt (DLTT) plus total debt in current liabilities (DLC)
Short-term $leverage_t$	Compustat	Total debt in current liabilities (DLC) in period t, scaled by the book value of total assets (AT) in period t
Long-term $leverage_t$	Compustat	Total long-term debt (DLTT) in period t, scaled by the book value of total assets (AT) in period t
Tobin's Q_t	Compustat	Market value of total assets scaled by the book value of total assets (AT) in period t, where market value of total assets is the book value of total assets (AT) minus the book value of equity (CEQ) plus the product of closing price (PRCC_F) and common shares outstanding (CSHO)
$R\&D_t$	Compustat	Research and development expense (XRD) in period t, scaled by the book value of total assets (AT) in period t
HP_t	Zillow	Median home value for square feet at the zip code level in period t using the year 2012 dollar values

Notes. Table 2.1 reports the variables used in this study. All data come from Compustat and Zillow, and data codes for Compustat are in parentheses.

Table 2.2 Descriptive Statistics

Variable	Total		High-tech sector		Non-high-tech sector	
	Mean	Median	Mean	Median	Mean	Median
Ln(Employee)	6.770	6.802	5.781	5.517	7.246	7.438
Ln(Sale)	19.13	19.29	17.95	17.90	19.69	19.92
R&D	0.0612	0	0.153	0.0943	0.0173	0
Cash	0.187	0.0973	0.330	0.280	0.118	0.0582
Leverage	0.252	0.191	0.177	0.0562	0.288	0.246
Tobin's Q	2.718	1.517	3.915	2.025	2.137	1.374
Size	5.502	5.500	4.598	4.418	5.937	6.070
Age	2.630	2.708	2.418	2.485	2.732	2.773
Size-Age Index	-4.102	-4.102	-3.445	-3.318	-4.418	-4.517
Whited-Wu Index	-0.262	-0.268	-0.213	-0.214	-0.286	-0.293

Notes. Table 2.2 shows the mean and median of variables across the total, high-tech sector, and non-high-tech sector samples. Variables are winsorized at the 1% level to account for outliers. Ln(Employee) is the natural log of the number of employees. Ln(Sale) is the natural log of the net sales using the year 2012 dollar values. R&D is the research and development expense, scaled by the book value of total assets. Cash is the cash and short-term investments, scaled by the book value of total assets. Leverage is the total debt, scaled by the book value of total assets. Tobin's Q is the market value of total assets, scaled by the book value of total assets. Size is the natural log of the book value of total assets. Age is the natural log of the difference between the fiscal year and the first year that the company appeared in Compustat. Size-Age index and Whited-Wu index are based on Hadlock and Pierce (2010) and Whited and Wu (2006), respectively.

Table 2.3 Speed of Labor Adjustment

	Full			High-tech	Non-high-tech
	OLS	Fixed Effect	System GMM	System GMM	System GMM
Dependent variable: Ln(Employee)$_{i,t}$					
Ln(Employee)$_{i,t-1}$	0.995***	0.792***	1.008***	0.997***	1.007***
	(0.001)	(0.003)	(0.007)	(0.011)	(0.009)
Capital$_{i,t-1}$	-0.022***	-0.111***	-0.027***	-0.098***	-0.025***
	(0.004)	(0.009)	(0.007)	(0.015)	(0.006)
Tobin's Q$_{i,t-1}$	0.019***	0.022***	0.030***	0.019**	0.022*
	(0.001)	(0.001)	(0.009)	(0.008)	(0.012)
CashFlow$_{i,t-1}$	0.171***	0.135***	0.132**	0.048	0.160*
	(0.007)	(0.008)	(0.059)	(0.053)	(0.082)
StockIssues$_{i,t-1}$	0.118***	0.081***	0.020	-0.178	0.146
	(0.012)	(0.013)	(0.107)	(0.111)	(0.130)
DebtIssues$_{i,t-1}$	0.139***	0.107***	-0.010	0.136	0.070
	(0.017)	(0.018)	(0.187)	(0.198)	(0.183)
Speed of Adjustment	0.005	0.208	0.008	0.003	0.007
M1 (p-value)	N/A	N/A	0	0	0
M2 (p-value)	N/A	N/A	0.833	0.951	0.828
Hansen J-test (p-value)	N/A	N/A	0.181	0.132	0.205
Diff-Hansen(p-value)	N/A	N/A	0.322	0.378	0.273
Observations	32,652	32,652	32,652	10,173	22,479
Year FE	Y	Y	Y	Y	Y
Firm FE	N	Y	Y	Y	Y

Notes. Table 2.3 shows the OLS model, fixed effect model, and system GMM model estimates of Equation (4) using the full sample. It shows the system GMM model estimates across high-tech and non-high-tech sector samples. Variables are winsorized at 1% level to account for outliers. Ln(Employee) is the natural log of the number of employees. Ln(Sale) is the natural log of the net sales using the year 2012 dollar values. Capital is the gross book value of property, plant, and equipment, scaled by the book value of total assets. Tobin's Q is the market value of total assets, scaled by the book value of total assets. CashFlow is the gross cash flow, scaled by the book value of total assets. StockIssues is the net cash inflow from stock issues, scaled by the book value of total assets. DebtIssues is the net cash inflow from debt issues, scaled by the book value of total assets. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.4 Demand Shocks on Firms

	Full	Full	Full	Full
	FE	FE	FE	FE
Dependent variable: ΔLn(Employee)$_{i,t}$				
Cash$_{i,t-1}$	0.203***	0.161***	0.155***	0.153***
	(0.052)	(0.052)	(0.053)	(0.053)
ΔLn(Sale)$_{i,t-1}$* Cash $_{i,t-1}$		-0.044***	-0.043***	-0.046***
		(0.011)	(0.011)	(0.011)
Leverage$_{i,t-1}$			-0.022	-0.016
			(0.041)	(0.042)
ΔLn(Sale)$_{i,t-1}$* Leverage$_{i,t-1}$				0.010
				(0.008)
ΔLn(Sale)$_{i,t-1}$	0.755***	0.755***	0.755***	0.755***
	(0.005)	(0.005)	(0.005)	(0.005)
Tobin's Q$_{i,t-1}$	0.000	-0.000	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.004)
Observations	32,652	32,652	32,652	32,652
Firms	3,471	3,471	3,471	3,471
Adjusted R-squared	0.751	0.751	0.750	0.750
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Notes. Table 2.4 shows a fixed effect model estimates of Equation (5) using the full sample. Variables are winsorized at 1% level to account for outliers. ΔLn(Employee) is the change in the natural log of the number of employees. Cash is the cash and short-term investments, scaled by the book value of total assets. ΔLn(Sale) is the change in the natural log of the net sales using the year 2012 dollar values. Leverage is the total debt, scaled by the book value of total assets. Tobin's Q is the market value of total assets, scaled by the book value of total assets. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.5 Demand Shocks on the High-Tech Sector

	High-tech	High-tech	High-tech	High-tech
	FE	FE	FE	FE
Dependent variable: $\Delta Ln(Employee)_{i,t}$				
$Cash_{i,t-1}$	0.251***	0.187***	0.174**	0.172**
	(0.070)	(0.069)	(0.071)	(0.071)
$\Delta Ln(Sale)_{i,t-1}$* $Cash_{i,t-1}$		-0.052***	-0.051***	-0.054***
		(0.014)	(0.014)	(0.013)
$Leverage_{i,t-1}$			-0.055	-0.045
			(0.072)	(0.078)
$\Delta Ln(Sale)_{i,t-1}$* $Leverage_{i,t-1}$				0.011
				(0.019)
$\Delta Ln(Sale)_{i,t-1}$	0.699***	0.699***	0.697***	0.697***
	(0.009)	(0.009)	(0.009)	(0.009)
Tobin's $Q_{i,t-1}$	0.001	0.001	0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	10,173	10,173	10,173	10,173
Firms	1,155	1,155	1,155	1,155
Adjusted R-squared	0.726	0.726	0.724	0.724
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Notes. Table 2.5 shows a fixed effect model estimates of Equation (5) using the high-tech sector. Variables are winsorized at 1% level to account for outliers. ΔLn(Employee) is the change in the natural log of the number of employees. Cash is the cash and short-term investments, scaled by the book value of total assets. ΔLn(Sale) is the change in the natural log of the net sales using the year 2012 dollar values. Leverage is the total debt, scaled by the book value of total assets. Tobin's Q is the market value of total assets, scaled by the book value of total assets. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6 Demand Shocks on the Non-High-Tech Sector

	Non-high-tech	Non-high-tech	Non-high-tech	Non-high-tech
	FE	FE	FE	FE
Dependent variable: $\Delta Ln(Employee)_{i,t}$				
$Cash_{i,t-1}$	0.135*	0.122	0.119	0.118
	(0.076)	(0.077)	(0.079)	(0.079)
$\Delta Ln(Sale)_{i,t-1}$* $Cash_{i,t-1}$		-0.025	-0.025	-0.028*
		(0.016)	(0.016)	(0.017)
$Leverage_{i,t-1}$			-0.000	0.002
			(0.042)	(0.043)
$\Delta Ln(Sale)_{i,t-1}$* $Leverage_{i,t-1}$				0.008
				(0.010)
$\Delta Ln(Sale)_{i,t-1}$	0.787***	0.787***	0.788***	0.788***
	(0.005)	(0.005)	(0.005)	(0.005)
Tobin's $Q_{i,t-1}$	-0.005	-0.005	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)
Observations	22,479	22,479	22,479	22,479
Firms	2,316	2,316	2,316	2,316
Adjusted R-squared	0.766	0.766	0.766	0.766
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Notes. Table 2.6 shows a fixed effect model estimates of Equation (5) using the non-high-tech sector. Variables are winsorized at 1% level to account for outliers. ΔLn(Employee) is the change in the natural log of the number of employees. Cash is the cash and short-term investments, scaled by the book value of total assets. ΔLn(Sale) is the change in the natural log of the net sales using the year 2012 dollar values. Leverage is the total debt, scaled by the book value of total assets. Tobin's Q is the market value of total assets, scaled by the book value of total assets. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 2.7 Demand Shocks on Firms

	Full	Large Positive Shock	Large Negative Shock
	IV	IV	IV
Dependent variable: ΔLn(Employee)$_{i,2006\text{-}2009}$			
ΔLn(Sale) $_{i,2006\text{-}2009}$	1.563	1.450	0.802*
	(3.781)	(2.021746)	(0.461)
Cash $_{i,2006}$* ΔLn(Sale)$_{i,2006\text{-}2009}$	8.682	-1.134	-1.071*
	(30.185)	(3.602)	(0.615)
Cash $_{i,2006}$	-3.941	-0.167	0.003
	(11.753)	(3.026)	(0.153)
Observations	2,109	105	1,392
Year FE	N	N	N
Firm FE	N	N	N

Notes. Table 2.7 shows the IV regression estimates of Equation (6) using the full, large positive shock, and large negative shock samples. Variables are winsorized at 1% level to account for outliers. ΔLn(Employee)$_{i,2007\text{-}2009}$ is the change in the natural log of the number of employees from 2007 to 2009. Cash$_{i,2006}$ is the cash and short-term investments in 2006, scaled by the book value of total assets in 2006. ΔLn(Sale)$_{i,2006\text{-}2009}$ is the change in the natural log of the net sales using the year 2012 dollar values from 2006 to 2009. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.8 Firms Characteristics Across the Speed of Adjustment Quartiles

Variable	Speed of Adjustment Quartile			
	1	2	3	4
Ln(Employee)	6.462	6.444	6.462	6.458
Ln(Sale)	18.78	18.78	18.78	18.72
R&D	0.0763	0.0728	0.0694	0.0596
Cash	0.203	0.208	0.194	0.170
Leverage	0.260	0.249	0.261	0.280
Short-term leverage	0.0621	0.0648	0.0698	0.0761
Long-term leverage	0.192	0.177	0.183	0.198
Tobin's Q	2.259	2.371	2.520	2.340
Size	5.237	5.252	5.152	5.050
Age	2.461	2.460	2.509	2.429
Size-Age Index	-3.900	-3.910	-3.840	-3.763
Whited-Wu Index	-0.242	-0.243	-0.241	-0.230

Notes. Table 2.8 shows the mean of variables across the speed of adjustment quartiles. Firms in the highest quartile adjust employment levels most quickly. Variables are winsorized at 1% level to account for outliers. Ln(Employee) is the natural log of the number of employees. Ln(Sale) is the natural log of the net sales using the year 2012 dollar values. R&D is the research and development expense, scaled by the book value of total assets. Cash is the cash and short-term investments, scaled by the book value of total assets. Leverage is the total debt, scaled by the book value of total assets. Short-term leverage is the total debt in current liabilities, scaled by the book value of total assets. Long-term leverage is the total long-term debt, scaled by the book value of total assets. Tobin's Q is the market value of total assets, scaled by the book value of total assets. Size is the natural log of the book value of total assets. Age is the natural log of the difference between the fiscal year and the first year that the company appeared in Compustat. Size-Age index and Whited-Wu index are based on Hadlock and Pierce (2010) and Whited and Wu (2006), respectively.

Table 2.9 Demand Shocks on Financially Constrained and Unconstrained Firms

	Firm R&D		Firm Size	
	High-tech	Non-high-tech	Small	Large
	FE	FE	FE	FE
Dependent variable: $\Delta Ln(Employee)_{i,t}$				
$Cash_{i,t-1}$	0.172**	0.118	0.185***	0.084
	(0.071)	(0.079)	(0.064)	(0.099)
$\Delta Ln(Sale)_{i,t-1}$* $Cash_{i,t-1}$	-0.054***	-0.028*	-0.042***	-0.038**
	(0.013)	(0.017)	(0.013)	(0.019)
$Leverage_{i,t-1}$	-0.045	0.002	-0.022	-0.067
	(0.078)	(0.043)	(0.064)	(0.054)
$\Delta Ln(Sale)_{i,t-1}$* $Leverage_{i,t-1}$	0.011	0.008	0.008	0.009
	(0.019)	(0.010)	(0.015)	(0.011)
$\Delta Ln(Sale)_{i,t-1}$	0.697***	0.788***	0.703***	0.808***
	(0.009)	(0.005)	(0.008)	(0.006)
$Q_{i,t-1}$	0.002	-0.005	0.005	-0.025***
	(0.005)	(0.005)	(0.005)	(0.006)
Observations	10,173	22,479	7,631	19,525
Firms	1,155	2,316	756	1,486
Adjusted R-squared	0.724	0.766	0.776	0.779
Test of Equality	7.09, *0.008*	7.09, *0.008*	2.80, *0.094*	2.80, *0.094*
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

Notes. Table 2.9 shows the fixed effect model estimates across different firm size. Variables are winsorized at 1% level to account for outliers. ΔLn(Employee) is the change in the natural log of the number of employees. Cash is the cash and short-term investments, scaled by the book value of total assets. ΔLn(Sale) is the change in the natural log of the net sales using the year 2012 dollar values. Leverage is the total debt, scaled by the book value of total assets. Tobin's Q is the market value of total assets, scaled by the book value of total assets. Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The Test of Equality reports t-tests and p-values (in italics) of tests of the null hypothesis that the coefficients on ΔLn(Sale)*Cash are the same for high-tech and non-high-tech firms, and for small and large firms.

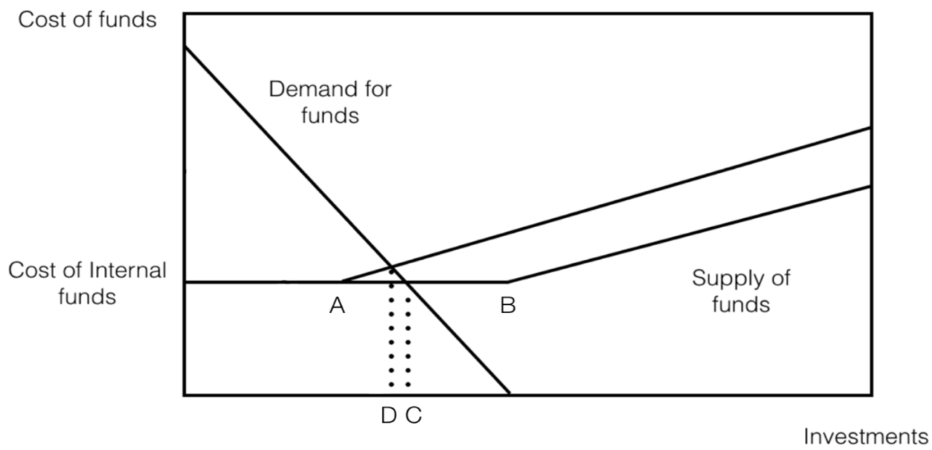

Figure 2.1 Constrained and Unconstrained Firms (Hall, 2002)

Notes. The downward-sloping curve in Figure 2.1 represents the demand for R&D investment funds. The upward-sloping curves represent the supply of R&D investment funds.

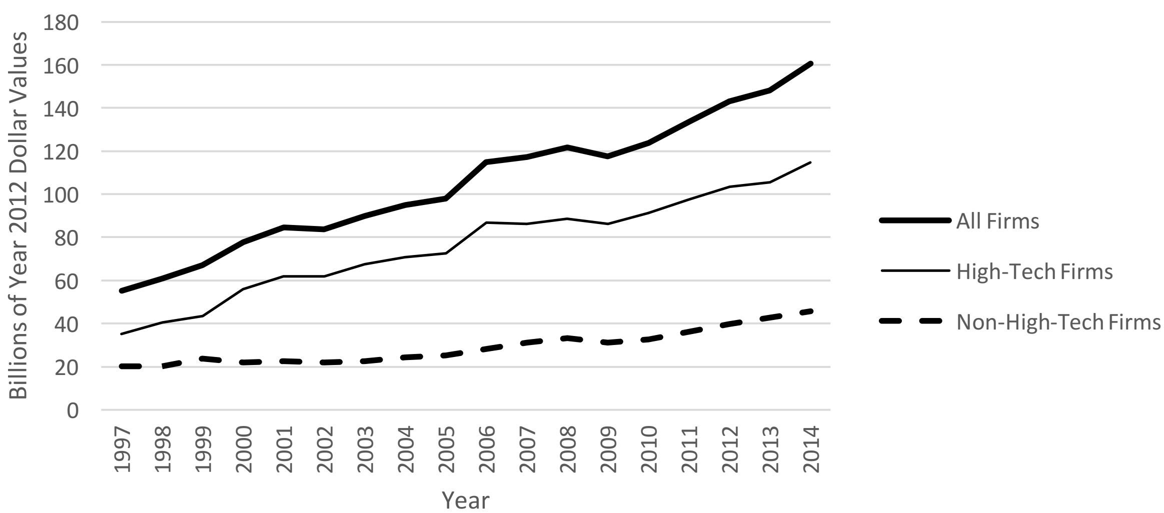

Figure 2.2 R&D Investment in U.S. Publicly Traded Firms

Notes. The thick line plots the sum of R&D investments of all publicly traded firms in the U.S. except the firms in the finance (SIC 60-69), public utilities (SIC 49), and public administration (SIC 90-99) industries. The following seven industries take account of 72% of the total R&D in the U.S. during the sample period: drugs (SIC 283), computer and office equipment (SIC 357), communications equipment (SIC 366), electronic components and accessories (SIC 367), laboratory instruments (SIC 382), medical instruments (SIC 384), and computer related services (SIC 737). This study defines the firms in these seven industries as high-tech firms (Brown et al., 2009; Brown et al., 2017). The thin line plots the sum of R&D investments of high-tech firms. The dashed-line plots the sum of R&D investments of non-high-tech firms, which are the rest of the firms.

CHAPTER 3. CONTRAST EFFECTS IN INVESTMENT AND FINANCING DECISIONS

The effects of context by a contrast stimulus, contrast effects, have not been extensively studied in a financial context. This study develops an experimental design to examine whether contrast effects distort the risk attitudes of individuals under a choice-based elicitation procedure. We find that individuals exposed to a positive stimulus amplify risk-seeking in investment decisions as opposed to individuals exposed to a negative stimulus. However, individuals behave similarly in making financing decisions regardless of different economic stimuli, which could suggest that financing decisions require a high cognitive load. On average, individuals spent 4% more time and changed their answers 4% more often in making financing decisions than investment decisions. The results suggest financing decisions may require a higher mental effort, and provide robust evidence that contrast effects can lead to mistakes in investment decisions.

Introduction

The effect of the behavior of individuals in financial markets is a rising concern in financial economics. In real-world situations, investors and managers are seldom replaced by programmed rational agents as assumed in the traditional models. The behavior of individuals is critical to address empirical puzzles in financial economics. This study uses the fourfold pattern of risk attitudes to examine the behavior of individuals.

The fourfold pattern of risk attitudes summarizes cumulative prospect theory (Tversky and Kahneman, 1992): risk seeking for gains of low probabilities, risk aversion for gains of high probabilities, risk aversion for losses of low probabilities, and risk seeking for losses of high probabilities. Tversky and Kahneman (1992) deviate from prospect theory and further develop cumulative prospect theory to support first-order stochastic dominance. Cumulative prospect theory posits that individuals overweight low-probability events and underweight high-probability events (Tversky and Kahneman, 1992). For instance, Kahneman (2011) shows individuals perceive an increase from 0% to 5% as more impressive than an increase from 5% to 10%. Although both intervals are quantitatively equal, the change from 0% to 5% is also a qualitative change, which is more impressive because it provides a possibility where none existed before. This possibility effect can explain why people put more weights in low-probability outcomes and buy lottery tickets. Another assumption for cumulative prospect theory is that individuals are risk-seeking for losses and risk-averse for gains. These assumptions lead to the fourfold pattern of risk attitudes.

This paper attempts to fill gaps in the literature of behavioral finance by addressing how contrast effects have an impact on investment and financing decisions, and how these results account for stock market crashes, frenzies, and security issuance decisions. Little is known of contrast effects in a financial context. Hartzmark and Shue (2016) attempt to provide evidence of how contrast effects distort prices in financial markets. They find that investors "mistakenly perceive earnings news today as more impressive if yesterday's earnings surprise was bad and less impressive if yesterday's surprise was bad" (Hartzmark and Shue, 2016). It is evident that a prior stimulus affects the behavior of individuals.

Inspired by the work of Hartzmark and Shue (2016), the experiment introduced in this paper uses a prior stimulus as a treatment. Also, the analysis is based on data using Amazon's Mechanical Turk (M-Turk) subjects. These subjects are individuals paid to perform small tasks over the Internet. These M-Turk subjects behave statistically similarly with students in lab environments or on the internet (Hoffman et al., 2018). The experimental design is based on the experiment using a choice-based elicitation procedure by Harbaugh et al. (2009). However, it is different in three ways: (i) this experiment takes place in a financial context by asking participants to choose between a stock and a bond, (ii) individuals are faced with investment and financing decisions, and (iii) some participants are exposed to a prior stimulus related to economic situations.

Several empirical puzzles can be addressed using the experimental results. First, some studies offer evidence that an increase in a firm's stock price leads to issuing more equity (Stein, 1996). Rational managers believe the firms are overvalued at its peak, so they try to take advantage of the high valuation by issuing more equity than bonds. According to the efficient market hypothesis, stock returns cannot be predicted. However, the correlation between issuing equity and stock returns is consistently negative and predictable empirically (Baker and Wurgler, 2000). Second, stock market prices can be overvalued, which can crash the stock market. Previous studies focus on the heterogeneity of agents. John List (2004) provides robust evidence that inexperienced traders are the cause of the distortion in prices because they tend to follow prospect theory rather than neoclassical theory.

We find that individuals exposed to a positive prior stimulus amplify risk-seeking in investment decisions. In other words, individuals exposed to an economic boom stimulus in the experiment are more likely to invest in equity than individuals exposed to an economic depression stimulus in the experiment. These results provide robust evidence that contrast effects can distort the behavior of individuals, which leads to inefficient stock markets. However, it is not evident that contrast effects influence financing decisions. It could be explained by a deliberative thinking, which leads to a high cognitive load, required for an unfamiliar task.

Background

Psychology studies show that some components help agents to form expectations. Anchoring is one of them. Individuals anchor on prior values when they make decisions. For instance, Kahneman and Tversky (1974) use a lab experiment to show an initial random number can influence estimating the percentage of African countries in the United Nations. Such anchoring studies are related to contrast effects.

Simonson and Tversky (1992) introduce two types of contrast effects. First, the local contrast effect shows how the addition of an element, z, in a set {x, y}, changes the attractiveness of y in contrast to x. For instance, y is preferred to z, but x is not clearly preferred to z. Then, adding z to the offered set increases the attractiveness of y in contrast to x. Second, the background contrast effect illustrates how past experience influences the attractiveness of y in comparison to x. This paper uses the background contrast effect to explain the distortion of investment and financing decisions following different economic stimuli that are no longer relevant to current decisions.

The background contrast effect is closely related to this study and influences current decisions. This effect is caused by past experience which is no longer relevant. Simonsohn and Loewenstein (2006) provide a field experiment based on the work of Simonson and Tversky (1992). In this field experiment, movers from expensive cities rent a higher price of apartments than movers from cheaper cities. Although previously observed prices are not relevant, movers from expensive cities feel that the current prices are cheaper taking account of wealth and taste. In this paper, signals of an economic condition such as pictures and articles are used as treatments. Such signals can be interpreted as narratives. Shiller (2017) defines narratives as explanations of events that can stimulate the emotions of individuals. If people experience strong emotions, these emotions can influence unrelated happenings

(Slovic et al., 2007). This paper ultimately shows that changes in the emotions of individuals influence decision making.

Model

Cumulative Prospect Theory

Kahneman and Tversky (1992) provide a way to assign the value of the gamble using cumulative prospect theory in Equation 1. x_i is an outcome, which happens with p_i probability. P_i represents the probability that an outcome takes a value greater than or equal to x_i, and P_i^* represents the probability that an outcome takes a value greater than x_i.

$$\sum \pi_i(p_i)v(x_i) \tag{1}$$

where

$$v(x_i) = \begin{cases} x_i^a \ if \ x_i \geq 0 \\ -\lambda(-x_i)^\alpha \ if \ x_i \leq 0 \end{cases} \tag{2}$$

$$\pi_i = w(P_i) - w(P_i^*) \tag{3}$$

$$w(P_i) = \ P_i^\gamma/[P_i^\gamma + (1 - P_i)^\gamma\ ]^{(1/\gamma)} \tag{4}$$

Previous experimental results provide the estimates of α, γ, and λ as 0.88, 0.65, and 2.25, respectively (Tversky and Kahneman, 1992). According to these experimental estimates, the relative sensitivity of losses is greater than that of gains. Also, the weighting function is an inverse-S-shaped curve as shown in Figure 3.1. It shows that individuals overweight a small probability and underweight a large probability. The empirical studies show that the absolute difference between the weight and the probability is largest when the probability is 0.1 and 0.8. The difference is smallest when the probability is 0.4 (see Fig. 1). Using the empirical estimates, Harbaugh et al. (2009) propose an experiment to test the fourfold pattern of risk attitudes.

The Fourfold Pattern of Risk Attitudes

This paper relies heavily on the experimental design using a choice-based elicitation procedure developed by Harbaugh et al. (2009). In their experiment, participants make six choices between a lottery and the expected value of the lottery as shown in Table 3.1. According to the fourfold pattern of risk attitudes, participants should be risk-seeking by choosing lotteries over expected values for prospects 1 and 6 in Table 3.1. On the other hand, participants should be risk-averse by choosing expected values over lotteries for prospects 3 and 4 in Table 3.1.

Hartzmark and Shue (2016) find that individuals perceive earnings news to be less or more impressive if the earnings surprises from the previous day were good or bad, respectively. These results show that a prior stimulus matters in the behavior of individuals. Inspired by their work, this study applies contrast effects into the experimental design developed by Harbaugh et al. (2009) to find whether contrast effects distort investment and financing decisions. For instance, some individuals are exposed to prior economic situations. According to contrast effects, news about an economic boom from one day will lead to earnings the next day looking less impressive. This makes earnings less of an incentive, and individuals become more risk-seeking (Holt and Laury, 2002). Analogously, news about economic depression from one day will make individuals more risk-averse the next. Simply put, it is anticipated that individuals exposed to a positive prior stimulus amplify risk-seeking over investment and financing decisions as shown in Table 3.2.

Experimental Design

This experiment tests how choices of individuals between a stock and a bond vary with the following treatments: an exposure to a picture related to an economic boom or depression, or an exposure to an article related to an economic boom or depression. It is designed to examine how each treatment affects choices of individuals between a stock and a bond. This paper closely relies on the experiment developed by Harbaugh et al. (2009).

In this experiment, we asked subjects to make three investment decisions and three finance decisions as if they were a manager of a firm. We randomly selected half of the participants to answer three investment questions first, and the other half answered three finance questions first. In each investment question, participants were given a choice to invest in either a bond or a stock. If they invested in the bond, future earnings would result in a certain return, which can be interpreted as a coupon payment in the real world. However, investing in the stock provided a risky return, which can be interpreted as a dividend payment in the real world. The risky return is either a higher return than the bond or no return at all. The following is an example of a part of an investment question:

Investing Decisions

"Now, you are given a choice to invest in either a bond (certain return) or a stock (risky return). If you choose to invest in the bond, your future earnings will be ₳50. If you choose to invest in the stock, your future earnings will be either ₳500 with 1/10 chance or ₳0 with 9/10 chance."

On the other hand, in each finance question, participants were given a choice to borrow money through issuing a bond or issuing a stock. If they borrowed money through issuing the bond, they paid a certain cost, which can be interpreted as a coupon payment to bond investors. Borrowing money through issuing a stock results in an uncertain cost. The uncertain cost is either a higher cost than the coupon payment to bond investors or no cost. An example of a part of a finance question is displayed below:

Financing Decisions

"Now, you are given a choice to borrow money by either issuing a bond (certain cost) or issuing a stock (uncertain cost). If you choose to borrow money by issuing the bond, your future earnings will be -₳50. If you choose to borrow money by issuing the stock, your future earnings will be either -₳500 with 1/10 chance or ₳0 with 9/10 chance."

There were 7 groups, and each group consisted of approximately 64 individuals. A total of 447 individuals in total were included in this study. Group A participated in tasks of choosing between a stock and a bond. Group B participated in tasks of choosing between a stock and a bond with an exposure to a picture related to an economic boom. Group C participated in tasks of choosing between a stock and a bond with an exposure to a picture related to an economic depression. Group D participated in tasks of choosing between a stock and a bond with an exposure to an article related to an economic boom. Group E participated in tasks of choosing between a stock and a bond with both an article and a picture related to an economic boom. Group F participated in tasks of choosing between a stock and a bond with an exposure to an article related to an economic depression. Group G participated in tasks of choosing between a stock and a bond with both an article and a picture related to economic depression. Table 3.3 illustrates the setup.

In this experiment, a survey dollar, ₳, was used. ₳1000 is equivalent to $1. Participants could have earned a maximum of $1.5 depending on one of the six choices they made. Individuals earned a minimum of $0.5. The final expected amount of compensation was $1. Table 3.4 summarizes the six choices that a participant faced in the experiment. For instance, individuals need to choose between a stock that can provide a 10% chance of receiving a $0.5 dividend and a bond that yields a $0.05 coupon payment. Table 3.5 summarizes the demographic information of M-Turk subjects. The mean demographic information of individuals in each group is about the same across groups. It shows that participants are randomly assigned to groups, and demographic characteristics cannot account for the results. On average, participants have a high school degree but not a bachelor's degree, and there are slightly more male participants. We performed logistic regression analyses for each group and found that the effect of demographic characteristics was not significant to our results.

This experiment is designed to compare the choices of participants exposed to economic boom conditions with the choices of participants exposed to economic depression conditions. Using the data collected from each group, we can find in what way each treatment affects how individuals choose between a stock and a bond.

Results

Table 3.6 compares the results by groups. We find that individuals are more likely to choose stocks for financing decisions than for investment decisions. In other words, people are more risk-seeking in financing decisions, which is consistent with cumulative prospect theory. Within investment decisions, a difference did exist based on stimuli. Individuals exposed to a picture of an economic boom are more likely to choose stocks, particularly low-probability stocks, than those exposed to a picture of an economic depression. However, the results of 22 percent and 14 percent, respectively, are statistically indistinguishable by the test of proportion (p-value: 0.29). As opposed to pictures, individuals exposed to an article behave similarly regardless of the economic condition described in the article. Individuals exposed to both pictures and articles of an economic boom are more likely to choose mid- and low-probability stocks. The results of 35 percent and 8 percent are statistically distinguishable according to the test of proportion (p-value: 0.00).

The results show that participants, whether statistically significant or not, are more likely to choose to invest in stocks following an economic boom. It implies that people are more risk-seeking in investment when a positive prior stimulus is applied. This leads to mistakes in investment decisions and raises prices of stocks above their fundamental values. These results directly address how contrast effects can explain stock market crashes and frenzies.

In the case of financing decisions, participants behave the same regardless of the economic condition they were exposed to. Possible explanations are described in the "Discussion and Conclusion" section.

Discussion and Conclusion

This study shows experimental evidence that a prior stimulus can influence the behavior of individuals in a financial context. As shown in Table 3.6, the distortion in the behavior of people affects investment decisions.

On the other hand, this study raises a question as to why contrast effects do not lead to mistakes in financing decisions. One possible explanation would be a difference in cognitive load between investment decisions and financing decisions. For instance, people may use different amounts of mental effort when they make different types of decisions. Table 3.7 shows the number of click counts that subjects made for investment and financing decisions. We can assume click counts is the number of time that subjects changed their answers. Subjects changed their answers 5.47 on average for financing decisions and 5.24 times on average for investment decisions. In other words, participants changed their answers 4% times more in making financing than investment decisions. Financing decisions could require a higher mental effort than investment decisions because people are less familiar with financing decisions. A higher cognitive load leads to less restraint on temptation and behavioral anomalies. Thus, unlike investment decisions, individuals are not influenced by treatments.

Also, individuals could use a naive rule when they make financing decisions because they are not used to it. When people face an unfamiliar task, they tend to apply a naive rule (Harbaugh et al., 2009). Table 3.7 shows that participants spent 4% more time to make financing decisions compared to investment decisions. On average, subjects took 122 seconds to make investment decisions but took 128 seconds to make financing decisions. This can lead to making financing decisions more difficult to be influenced by treatments. Another reason can be a division of cognitive processes. Kahneman (2011) argues that individuals use two systems of thought. System 1 produces reactions that require no effort, and System 2 requires more deliberative thinking. However, it is not observable which System subjects use. Using the time it took for first clicks on all questions, we can see what decisions need more reaction time; it took subjects 34 seconds and 45 seconds to make their first investment and financing decisions, respectively. It could be possible that financing decisions require more deliberative thinking by using System 2. Thus, treatments could affect the financing decisions less.

Findings from this paper raise some questions about financing decisions. Further studies can explain why individuals with different stimuli behave the same in financing decisions. However, it is evident that contrast effects can lead to mistakes in investment decisions. These results show that contrast effects help solve equilibrium puzzles in financial economics.

Figures and Tables

Table 3.1 The Six Prospects

Prospect Number	Lottery	Expected Value	FFP Risk Attitude
1	1/10 of +$20, 9/10 of +$0	$2	Seeking
2	4/10 of +$20, 6/10 of +$0	$8	Neutral
3	8/10 of +$20, 2/10 of +$0	$16	Averse
4	1/10 of -$20, 9/10 of +$0	-$2	Averse
5	4/10 of -$20, 6/10 of +$0	-$8	Neutral
6	8/10 of -$20, 2/10 of +$0	-$16	Seeking

Table 3.2 Payoff Matrix with Treatments

Type	Stock	Bond	FFP Risk Attitude	Predicted Risk Attitude (Economic Boom)	Predicted Risk Attitude (Economic Depression)
Investing Decisions	1/10 of +$0.5, 9/10 of +$0	$0.05	Seeking	More Seeking	Less Seeking
	4/10 of +$0.5, 6/10 of +$0	$0.2	Neutral	Neutral	Neutral
	8/10 of +$0.5, 2/10 of +$0	$0.4	Averse	Less Averse	More Averse
Financing Decisions	1/10 of -$0.5, 9/10 of -$0	-$0.05	Averse	Less Averse	More Averse
	4/10 of -$0.5, 6/10 of -$0	-$0.2	Neutral	Neutral	Neutral
	8/10 of -$0.5, 2/10 of -$0	-$0.4	Seeking	More Seeking	Less Seeking

Table 3.3 Group Matrix

	No Pictures	Economic Boom Pictures	Economic Depression Pictures
No Articles	Group A	Group B	Group C
Economic Boom Articles	Group D	Group E	x
Economic Depression Articles	Group F	x	Group G

Table 3.4 Payoff Matrix

Type	Stock	Bond	FFP Risk Attitude
Investing Decisions	1/10 of +$0.5, 9/10 of +$0	$0.05	Seeking
	4/10 of +$0.5, 6/10 of +$0	$0.2	Neutral
	8/10 of +$0.5, 2/10 of +$0	$0.4	Averse
Financing Decisions	1/10 of -$0.5, 9/10 of -$0	-$0.05	Averse
	4/10 of -$0.5, 6/10 of -$0	-$0.2	Neutral
	8/10 of -$0.5, 2/10 of -$0	-$0.4	Seeking

Table 3.5 Demographic Information

Mean (Std.)	Group A	Group B	Group C	Group D	Group E	Group F	Group G
Observation	64	65	63	60	68	61	66
Age	40.17 (10.70)	39.69 (10.59)	39.71 (11.85)	39.88 (10.70)	39.87 (11.15)	39.93 (10.20)	40.24 (10.78)
Education	1.84 (0.74)	1.82 (0.79)	1.79 (0.81)	1.85 (0.71)	1.69 (0.63)	1.95 (0.74)	1.83 (0.65)
Gender	1.59 (0.46)	1.38 (0.49)	1.63 (0.52)	1.48 (0.50)	1.60 (0.49)	1.52 (0.50)	1.56 (0.50)

Notes: Gender is a variable, where 1 means female and 2 means male. Education is a variable between 1 and 4, where 1, 2, 3, and 4 represent High School, Bachelor’s Degree, Master’s Degree, and Ph.D. Degree, respectively.

Table 3.6 Proportion of Stock by Treatments

Comparison Between Groups Exposed to Economic Boom and Depression Pictures

Type	Stock	Bond	Proportion of Stock	
			Group B (Boom)	Group C (Depression)
Investing Decisions	1/10 of +$0.5, 9/10 of +$0	$0.05	0.22	0.14
	4/10 of +$0.5, 6/10 of +$0	$0.2	0.22	0.22
	8/10 of +$0.5, 2/10 of +$0	$0.4	0.42	0.33
Financing Decisions	1/10 of -$0.5, 9/10 of -$0	-$0.05	0.29	0.44
	4/10 of -$0.5, 6/10 of -$0	-$0.2	0.29	0.40
	8/10 of -$0.5, 2/10 of -$0	-$0.4	0.42	0.44

Comparison Between Groups Exposed to Economic Boom and Depression Articles

Type	Stock	Bond	Proportion of Stock	
			Group D (Boom)	Group F (Depression)
Investing Decisions	1/10 of +$0.5, 9/10 of +$0	$0.05	0.20	0.28
	4/10 of +$0.5, 6/10 of +$0	$0.2	0.25	0.23
	8/10 of +$0.5, 2/10 of +$0	$0.4	0.40	0.41
Financing Decisions	1/10 of -$0.5, 9/10 of -$0	-$0.05	0.28	0.30
	4/10 of -$0.5, 6/10 of -$0	-$0.2	0.35	0.26
	8/10 of -$0.5, 2/10 of -$0	-$0.4	0.43	0.52

Comparison Between Groups Exposed to Economic Boom and Depression Pictures and Articles

Type	Stock	Bond	Proportion of Stock	
			Group E (Boom)	Group G (Depression)
Investing Decisions	1/10 of +$0.5, 9/10 of +$0	$0.05	0.35***	0.08***
	4/10 of +$0.5, 6/10 of +$0	$0.2	0.29**	0.14**
	8/10 of +$0.5, 2/10 of +$0	$0.4	0.32	0.45
Financing Decisions	1/10 of -$0.5, 9/10 of -$0	-$0.05	0.37	0.30
	4/10 of -$0.5, 6/10 of -$0	-$0.2	0.37	0.30
	8/10 of -$0.5, 2/10 of -$0	-$0.4	0.41	0.50

Notes: *** and ** represent p-values smaller than 0.01 and 0.05, respectively. P-values of the test of proportion for having the same proportions across two groups are reported.

Table 3.7 Time and Click Counts
Comparison Between Investment and Financing Decisions

Type	Investment Decisions	Financing Decisions	Paired T-Test
	Mean	Mean	Two-sided p-value
First Click Time	34.41	44.55	0.00
Page Submit Time	122.32	127.61	0.02
Click Counts	5.24	5.47	0.03

Notes: Variables are winsorized at 5% level before taking a mean to account for outliers. First click time represents the total number of seconds that individuals initially took to click for all questions. Page submit time represents the total number of seconds that individuals finished all questions. Click counts represents the number of clicks that subjects made for all questions.

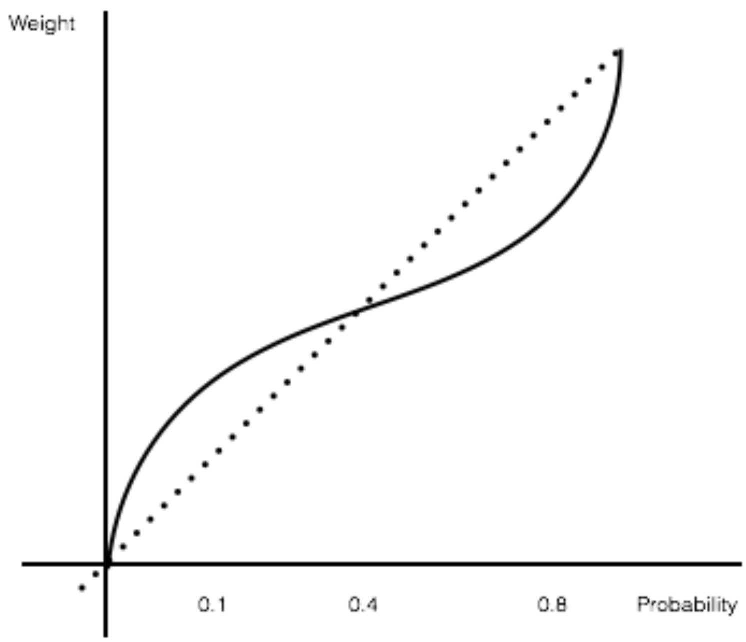

Figure 3.1 Weighting Function

CHAPTER 4. EMERGENCE OF GOODS AS MEDIA OF EXCHANGE IN DIFFERENT TYPES OF TRADE NETWORKS

This study uses an agent-based computer model to examine how trade networks influence the emergence of goods as media of exchange in a decentralized economy. This model implements the evolutionary process of the Kiyotaki-Wright (KW) model (1989), which explains the endogenous emergence of multiple media of exchange. Unlike previous experimental findings, this paper finds that all the agents behave according to the KW model, where some agents prefer to accept a higher storage cost good over a lower storage cost good because they speculate having a shorter wait for trading their consumption goods. In this study, the KW model is expanded to different types of trade networks, and shows that trade networks can cause agents to adopt speculative strategies. This leads to the emergence of multiple goods as media of exchange across different trade networks.

Introduction

Networks have been defined as "a collection of entities together with a specified pattern of relationships among these entities" (Tesfatsion, 2008). There are varieties of networks across all domains of life. For instance, the Internet forms a technological network that connects everyone around the world. Friends can also form a social network. Likewise, the Seoul Metropolitan Subway forms a transportation network that is connected to various destinations in Seoul. More recently, a Bitcoin network has emerged connecting multiple Bitcoin clients that contain transaction information.

Each Bitcoin client, or node, shares information regarding transactions. Thus, information on transactions is decentralized and protected from failure of individual nodes. However, the underlying Bitcoin network formations are still abstract. Individuals seldom store their Bitcoin purchases in a private client, but rather use an online platform like

Coinbase to store their purchases. This platform, on the other hand, makes this decentralized Bitcoin network somewhat unprotected because the platform hosts multiple transactions on behalf of different users. This paper studies how different types of networks influence the emergence of money in terms of speed and media of exchange.

New media of exchange may arise at any time in any context. Money has three main roles such as a medium of exchange, a unit of account, and a store of value (Kiyotaki and Wright, 1989; Doepke and Schneider, 2017; He et al., 2019). This study focuses on the medium of exchange role of money. Why do there exist multiple media of exchange, where some are dominated in rate of return by others? The characteristics of goods used as media of exchange in a decentralized economy have been frequently studied by many monetary theorists. Kiyotaki and Wright (1989) provide a simple search model that can explain the existence of multiple media of exchange, and show that not only intrinsic properties like storage costs but also extrinsic beliefs like marketability of goods cause certain goods to be used as media of exchange. Because of its simplicity, the KW model has been mainly used to study the emergence of goods as media of exchange.

In the Kiyotaki-Wright (hereafter KW) model (1989), there are three types of agents (Type 1, Type 2, and Type 3) and commodities (Good 1, Good 2, and Good3). The goods are indivisible and storable, and the agents with unit mass are assumed to live infinitely. Each type of agents is specialized in consumption and production: Type 1 only gains positive utility from consuming Good 1. Type 1 can neither consume nor derive positive utility from consuming other types of goods. Similarly, Types 2 and 3 gain positive utility from consuming Goods 2 and 3, respectively. On the other hand, Type 1 produces Good 2. Likewise, Types 2 and 3 specialize in the production of Goods 3 and 1 respectively. Before trading occurs, no agent produces a good that is consumable to the agent who produces his consumption good. This unique setting leads to the absence of double coincidence of wants. Therefore, to obtain the consumption good, each agent must trade and accept a good that is not his consumption good.

The non-consumption good used for the trade is known as a medium of exchange. In the KW model, there are two types of equilibrium as shown in Figure 4.1 and 4.2: a fundamental equilibrium and a speculative equilibrium. In the fundamental equilibrium, one good emerges as a medium of exchange, but the other equilibrium yields two goods as media of exchange. However, the KW model assumes agents start interacting with each other with an equilibrium belief. Thus, many economists like Basci (1999), Duffy (2001), Marimon et al. (1990), and Luo (1998) use evolutionary processes to test whether the model is valid, even if agents begin trade without the equilibrium belief.

Learning algorithms such as learning by imitation (Basci, 1999) and learning by past experience (Duffy, 2001) are employed to study the KW model. However, most of these studies have found that one type of agent, Type 1, does not accept a higher storage cost good over a lower storage cost good regardless of expecting a shorter wait for trading consumption goods like the KW Nash equilibrium prediction. Using a modified version of Duffy's learning algorithm, which is based on experimental findings (Duffy and Ochs, 1999), this paper shows the agent-based computer model that is consistent with the KW model. Some agents adopt speculative strategies, which leads to the emergence of multiple goods as media of exchange.

Using the agent-based computer model as a base model, I integrate the KW model into Wilhite's four different trade networks: Global Networks, Local Disconnected

Networks, Local Connected Networks, and Small-world Networks. In terms of Wilhite's model, the base model is formed in a Global Network. However, Wilhite (2001) argues that the Small-world Network is the closest to a real-world networks system, because agents can trade locally with low transaction cost of exchange while resources are globally allocated. This study finds that the emergence of goods as media of exchange varies with different types of trade networks.

Literature Review

Previous research does not clearly explain how trade networks affect the KW model. Most studies on the KW model have focused on the theoretical extensions of the model and the Nash equilibrium prediction of the model in a dynamic framework using two different approaches: laboratory experiments with human subjects and agent-based computer models.

Theoretical Models

There have been many attempts to explain the endogenous emergence of money as a medium of exchange. Because of its simplicity, the KW model has dominated the literature in monetary economics since it was first introduced. However, Jones (1976) was the first economist to formulate the emergence of money as a medium of exchange in a barter economy. The KW model is an extension of Jones' framework. In both models, agents are paired randomly and make decisions on whether to trade or not in a trade round. Jones (1976) points out that the most crucial factor of a medium of exchange is how relatively common a good is, rather than other intrinsic attributes. However, Jones' model imposes heavy restrictions on the behaviors of agents in choosing efficient trading strategies.

Smith (1776) observes that money originates from the division of labor, which implies that some frictions in trade are required to build a model of the emergence of a medium of exchange. Rupert, Schindler, and Shevchenko (2000) define these frictions in their survey. They state, “these frictions include the following: agents are not always in the same place at the same time; there is no way to enforce long-run commitments (unless they are dynamically incentive compatible); and that agents are anonymous in the sense that their histories are not public information.”

In the KW model, agents specialize in the production of one type of good and the consumption of another specific type of good. A trade occurs bilaterally when both traders mutually agree. This setting leads to the double coincidence of wants problem (Jevons, 1875) in which agents eventually face indirect barter. Agents try to maximize expected discounted future utilities by choosing appropriate trading strategies. Multiple equilibria do not arise for any parameter values. When all the agents behave according to a fundamental trading strategy by only trading one good for a lower-storage-cost good, the steady-state pattern of exchange yields a fundamental equilibrium. On the other hand, the best response for certain agents may be to trade for higher-storage-cost goods by speculating a shorter wait for acquiring their own consumption goods. This behavior is called a speculative trading strategy.

Kiyotaki and Wright (1989) provide characteristics of the Nash equilibria in trading strategies. For all parameter values, the best responses of Types 2 and 3 are to behave fundamentally. However, Type 1 uses the speculative trading strategy for certain parameterizations. This equilibrium is called a speculative equilibrium. In the fundamental equilibrium, a single good emerges as a medium of exchange. This good has the lowest-storage-cost, implying that the intrinsic value of goods acts crucially to become media of exchange. However, the speculative equilibrium leads to the emergence of multiple goods as media of exchange, which suggests that one of the media of exchange will inevitably dominate the others. This is a unique finding that can explain the real-world question why we use money in economies in which many financial assets with lower rates of return than money exist.

New monetarist economists have considered some theoretical extensions of the KW model. For example, Aiyagari and Wallace (1991) use the coexistence of commodity money and fiat money, which is a good with no consumption and production value in an exchange economy. He, Huang, and Wright (2005) create a simple model to study the emergence of banking and money using the KW model. Lagos and Rocheteau (2008) also investigate an economy where commodity money and fiat money coexist as a medium of exchange, and research certain conditions in which valued fiat money improves welfare.

Laboratory Experiments with Human Subjects

Earlier studies on the KW model are devoted to the model in a dynamic framework because it is a simple model to learn that agents starting without equilibrium beliefs learn to adopt efficient trading strategies over time. Brown (1996) implements the human-subject experiment of the KW model to find out if money emerges as a medium of exchange according to the Nash equilibrium prediction. He uses 36 subjects, 50 rounds, and the framework based on the agent-based computer model built by Marimon, McGrattan, and Sargent (1990). There exist some deviations from the prediction in the experiment because only some of Type 1s learn to play speculative trading strategies. He believes the lack of information provided to agents in the experiments may be the cause of the problem.

Duffy and Ochs (1999) use another laboratory experiment to verify the Nash equilibrium prediction of the KW model in a dynamic framework. Changing the parameter values of utility functions and the initialization schemes, they look for contradictions to the theory. Unlike Brown's experiment (1996), this model does not exclude any features from the KW model, such as agents' risk attitudes and discounting assumptions. However, employing an infinite number of subjects is not available in a lab experiment setting. Therefore, a finite number of subjects, due to the constraint of the lab capacity, 18, 24, or 30, is used in the experiment. The findings from this human-subject experiment show that the individuals who are supposed to speculate adapt to learn fundamental trading strategies. Duffy and Ochs (1999) believe that this disagreement emerged because individual made decisions based on trading history, not the marketability of goods. Hazlett (2003) replicates this experiment using students in his undergraduate class, and comes to the same conclusion.

Agent-Based Computer Models

Learning behavior

Agent-based computer models can substitute for human subjects to investigate the evolutionary development of the KW model. Marimon, McGrattan, and Sargent (1990) attempt the first simulation of the KW model using artificially intelligent agents. They modified a few aspects in their agent-based computer model to be more similar to human subjects. First, finite numbers of agents exist in the decentralized economy. Second, the agents try to maximize the average level of utility instead of expected discounted future utilities as in the KW model. Last, the agents make trading and consumption decisions based on Holland (1975) classifier systems. A system is a set of rules, and agents choose the rule which has generated the best payoff. They basically learn by experience, so the strength of rules evolves dynamically. When it is not efficient to store all the decision rules, agents make decisions based on the extended version of the genetic algorithm of Holland (1975). Using these behavioral rules, he finds that most agents behave as in the Nash equilibrium prediction of the KW model. However, in an economy where certain agents are parameterized to trade for goods with higher storage cost by expecting shorter waits for their consumption goods, speculative trading strategies do not emerge.

Basci (1999) extends their work by introducing a new type of learning algorithm for the KW model. He also believes agents learn by imitating social values. Using this behavioral rule, he finds that the speed and probability of convergence with the Nash equilibrium increases. Also, a speculative equilibrium is observed with the presence of imitation behavior. Luo (1998) studies the emergence of money as a medium of exchange using a different learning algorithm. To compensate for the defect of agents' myopic strategies, she uses the notion of Darwinian dynamics in which superior strategies survive in the economy over time. She concludes that extrinsic beliefs which determine the initial trading strategies and intrinsic value like storability play an important role in the emergence of money as a medium of exchange. This result supports the findings of Kiyotaki and Wright (1989).

Duffy (2001) derives a simplified learning behavioral rule of agents from the results of human-subject experiments. Using the nature of that rule, he has developed an agent-based computer model employing the evolutionary approach to test the Nash equilibrium prediction of the KW model. The agent-based computer model allows observation of both individual and aggregate behaviors in a dynamic framework. Although communication between artificial agents is not present in the model, the agent-based computer model closely follows human-subject experiments, and is built most closely on KW model. As in the experiment with human-subjects implemented by Duffy and Ochs (1999), 18 or 24 agents are used in the agent-based computer model for the comparison of the results. In the agent-based computer model, Duffy (2001) uses an initialization scheme that considers the distribution of initial goods in every game using the steady-state proportion. Using a logistic model for behavioral rules, Duffy (2001) notes that individual agents' behaviors tend to adhere to the initial trading strategy throughout the whole game. Contrasted with Kiyotaki and Wright's conclusion, the evidence from both the agent-based computer model and the human-subjects experiment indicate that an agent, whose best response is to adopt speculative trading strategies under certain parameterization, learns to adopt a fundamental trading strategy.

Since the results of the agent-based computer model and human-subject experiments are similar, Duffy (2001) not only designs and compares the agent-based computer model with human-subject experiments, but also extends the KW model by attempting two modifications to obtain results close to the prediction of Kiyotaki and Wright (1989). First, he increases the proportion of Type 3s in the economy, which allows Type 1s to encounter more speculative trading opportunities. Second, the behaviors of Types 2 and 3 are no longer dependent on past history, but they are forced to trade using fundamental trading strategies. This reinforcement eliminates any outliers in trading behaviors of Types 1 and 3. Both modifications significantly increased the percentage offer frequencies of Type 1 by using speculative strategies in the agent-based computer model and the new human-subject experiment. Importantly, the speed of learning increased more in the second treatment.

Some economists have introduced modified environments to the KW model. For example, Yang, Kwon, Jung, and Kim (2008) built an agent-based computer model allowing agents initially to start with more than one good in their inventories. They use different qualities of goods representing salability to find out the most influential characteristics. When interpreted using a spanning tree, this model reveals that intrinsic value like storage costs are more important than other attributes of a medium of exchange. Pospelov and

Zhukova (2009) extend the KW model by allowing agents to produce goods over time. With an agent-based computational approach, they find out that using money, a good with no consumption value for trade, benefits agents more than using barter. Newhouse (2007) investigates how a commodity arises as a medium of exchange in a barter economy with trading posts. This model is an alternate approach to study the emergence of money because the KW model only considers a pure exchange economy. He finds out the important characteristics of commodity money are "high trading volume and low trading cost" (Newhouse, 2007, p.1).

Trading networks

Other economists have raised questions about how trading networks influence the equilibrium patterns. Wilhite (2001) uses agent-based computer models to study price dynamics and the efficiency of resource allocation in four different types of trade networks: a Global Network, a Local Disconnected Network, a Local Connected Network, and a Small-world Network (Watts and Strogatz, 1998). He uses a simple barter economy in which agents try to maximize their utility using the Cobb-Douglas utility function composed of two types of goods. In every trade round, each agent looks for an appropriate partner to haggle the price of one good. After establishing a price, they trade until the benefits of the agreement decrease for one agent. Next, they look for another partner who benefits mutually, and repeat the previous procedure.

Wilhite (2001) has characterized the search, negotiation and exchange activities of each network equilibrium. As shown in Figure 4.3, Wilhite (2001) places all the agents around the rim of a circle for the purpose of efficiency. In the Global Network, traders can communicate with all other traders, and only a few trades are required to optimize global resources. However, this globalized trade network incurs high search and negotiation costs. In the Local Disconnected Network, each agent is only allowed to trade with a subset of the overall population. This leads to a decrease in search costs, but multiple price equilibria emerge across the trade groups. The Local Connected Network shares a similar structure property with the Local Disconnected Network, but two members of each trade group overlap with neighboring trade groups. Although agents keep trading locally, global resources move around entire trade groups over time. This implies that the Local Connected Network possesses both local and global trading properties. In the end, the highest search costs of all the trade networks seem to arise in the Local Connected Network, but only one price equilibrium shows up across trade groups in this network.

A Local Connected Network with crossovers between distant trade groups is called a Small-world Network (Watts and Strogatz, 1998). In this trade network, search costs go down significantly, although it takes more time to achieve a price equilibrium than in the Global Network. This trade network has advantages of both local and global trade networks. Two properties of the Small-world Network are observed in the simulation: First, as path length, which is "defined as the minimum number of exchange required for an agent to trade with every agent in the population" (Wilhite, 2001, p.59), increases, the convergence of the equilibrium price slows down. Second, group size has a positive correlation between search and negotiation costs. He also argues that Crossover Agents who can communicate with distant trade groups accumulate more wealth than others. This is a big incentive to form such trade networks. Wilhite (2001) asserts that this trade network occurs "in nature and may help explain the ease with which most of us acquire goods from around the world."

Kunigami, Kobayashi, Yamadera, and Terano (2009) have developed a new model with a new trading network (called the micro-macro doubly structural network) in order to investigate the emergence of goods as media of exchange. Each agent has access to a social network and micro networks. This network is based on the Star-shaped Network developed by Starr (2003). This network structure is a closer approximation of real society. They use two approaches to verify this model: mean-field approximation of dynamics and agent-based simulation. Agents learn by imitating, trimming, conceiving and forgetting. Using this model, Kobayashi, Kunigami, Yamadera, Yamada, and Terano (2009) find that a change in a social network structure influences the speed of the emergence of money.

Giansante (2007) changes the trade network structures of a modified KW model using an evolutionary approach to find out how the network properties influence the Nash equilibrium prediction. When he builds the artificial environment, he allows agents to store more than one good without assigning storage and transportation costs to goods. He believes that these intrinsic properties do not matter in the emergence of a good as a medium of exchange. Also, he uses the replicator dynamic process developed by Mailath (1992) to program the behavior of agents. It is similar to the learning model Basci (1999) employed in the context of imitation. However, the replicator dynamic system only allows a certain fraction of agents with low wealth to replicate the behavior of agents with higher wealth. As the connectivity between networks increases, multiple media of exchange converge to one medium of exchange. Also, he observes that the wealth of agents in the networks improves as the connectivity increases. On the other hand, the degree of connection between networks decreases and multiple media of exchange tend to emerge in the economy. These results evidently predict that changes in trade network structures influence the emergence of a medium of exchange.

Model

The Kiyotaki-Wright Model

The economy is composed of infinitely repeated discrete time periods. Encountering the first-time period, the agents start with a single unit of good in their storages. Type i denotes an agent type i, where i is a variable in mod 3. Good $i+1$ denotes the production good for Type i, Good $i+2$ denotes the other non-consumption good for Type i, and Good i denotes the consumption good for Type i. They are allowed to store one unit of a good in every period. In the beginning of a period, each agent enters a trade round where they are randomly paired, and faced with the decision of whether to trade the good in the storage or not. If both agents offer to trade, they exchange the good in their storage. After the trade round, they have to decide whether to consume the exchanged good. If an agent Type i trades the goods in the storage for Good i, the agent consumes the good, produces Good $i+1$, and stores it in the storage at the end of the trade round. If the paired agents neither mutually agree on trade nor trade for Good i, they keep the goods in storage without consumption until the next trade round. Expecting a shorter wait to trade for Good i, the agents sometimes will offer to trade for Good $i+2$. In this case, the good for which the agent traded is known as a medium of exchange. Kiyotaki and Wright (1989) show the endogenous emergence of a commodity as a medium of exchange. Each agent makes a trading decision in every trade round by choosing a trading strategy which maximizes the utility value using the objective function below. The expected discounted lifetime utility of Type i is given by

$$\mathrm{E}\sum_{t=0}^{\infty}\beta^{t}(I_i(t)u_i - I_{i+1}(t)c_{i+1} - I_{i+2}(t)c_{i+2})$$

where $\beta^t \in (0,1)$ is the discount factor in time t, u_i is the instantaneous utility from consumption. c_{i+1} and c_{i+2} are costs of storing Good $i+1$ and Good $i+2$, respectively. I only consider Model A from the KW model where $0 < c_1 < c_2 < c_3$ for all types of agents. If the agents do not consume a good in time, t, $I_i(t)$ takes on the value of zero. Otherwise, $I_i(t)$ takes on the value of 1. Likewise, $I_{i+1}(t)$ and $I_{i+2}(t)$ take on the value of zero unless Type i stores Good $i+1$ and Good $i+2$, respectively, in time *t*.

Kiyotaki and Wright (1989) characterize the Nash equilibrium in trading strategies. When the agents face the partner holding the consumption good, the dominant strategy is to offer to trade. Let $s_i \in \{0,1\}$ denote the trading strategy of Type i. If Type i offers to trade Good $i+1$ (the production good) for Good $i+2$ (the other non-consumption good), $s_i = 1$. If the agent refuses to trade Good $i+1$ for Good $i+2$, $s_i = 0$. For example, if Type 1 refuses to trade Good 2 for Good 3, Type 1's trading strategy becomes 0. On the other hand, if Type 1 offers to trade Good 2 for Good 3, Type 1's trading strategy becomes 1.

$$(1)\ (c_3 - c_2) > [p_3 - (1 - p_2)]\beta u/3$$

Inequality (1) represents that the difference between the storage costs of Goods 3 and 2 are greater than the marketability benefits of storing Good 3 over Good 2. The proportion of Type i, entering the trade round with Good $i+1$ is referred as p_i. If inequality (1) holds, a Type 1 with Good 3 will offer to trade for Good 2. The agent is willing to trade a good with a higher storage cost for the good with the least storage cost. This trading strategy is called a fundamental trading strategy because the trading decision is only based on one fundamental factor, storage costs.

$$(2)\ (c_3 - c_2) > (0.5)\beta u/3$$

The fundamental equilibrium is characterized by the vector of strategy, $s_i = (0,1,0)$: The first number, 0, in the 3-tuple represents that Type 1 refuses to trade its production good, Good 2, for the other non-consumption good, Good 3. The second number, 1, represents that Type 2 offers to trade Good 3 for Good 1. The third number, 0, represents that Type 3 refuses to trade Good 1 for Good 2. In this fundamental equilibrium, all the agents use fundamental trading strategies. When parameterization satisfies inequality (2), the fundamental equilibrium arises. This pattern of exchange is displayed in Figure 4.1. This figure shows that Type 2 accepts Good 1 from Type 3 even if Good1 is not the consumption good of Type 2. In other words, in the fundamental equilibrium, only one type of good, Good 1, emerges as a medium of exchange.

$$(3)\ \left(c_3 - c_2\right) < \left(\sqrt{2} - 1\right)\beta u/3$$

However, multiple types of goods emerge as media of exchange when inequality (3) holds. Using the other steady state vector of the proportion, $p = (0.5\sqrt{2}, \sqrt{2} - 1, 1)$, when parameterization satisfies inequality (3), the speculative equilibrium arises. When the agents are willing to trade a good with higher storage cost for a least storage cost good – expecting a shorter wait to trade for the consumption good – the trading strategy is called a speculative trading strategy. The speculative equilibrium is also characterized by the vector of strategy, $s_i = (1,1,0)$: Type 1 offers to trade Good 2 for Good 3. Type 2 offers to trade Good 3 for Good 1 and Type 3 refuses to offer to trade Good 1 for Good 2. This pattern of exchange leads to the emergence of Goods 1 and 3 as media of exchange. The pattern of exchange in the speculative equilibrium is shown in Figure 4.2.

Experimental Design

Artificial environments

As in the Kiyotaki-Wright economy, the artificial environment used in this paper is composed of an equal number of each of three types of agents and goods. The total number of artificial agents is divisible by six so that they can be paired without left over agents. Employing 24 artificial agents in the agent-based computer model allows comparison with Duffy's findings. One of the advantages of using an agent-based computer model, unlike the experiment with human subjects, is the efficiency in scaling the number of agents. A total of 24, 48, 72 or 96 artificial agents will make up the entire economy. The same parameter values are used from Duffy's model (2001). However, I have extended the model by including additional parameter values, as shown in Table 4.1.

Every agent is randomly placed in the rim of a circle. Figure 4.3 shows how agents are paired in each trade network. The trade networks differ in how easily agents can find a trading partner. In the Global Network, all the agents have a chance to trade with every other agent in the circle with the same search cost. In the Local Disconnected Network, the population is divided into groups. Agents can only trade with partners within their group, and so trade across groups is prohibitively costly. The Local Connected Network has the same features as the Local Disconnected Network except that the agents located at the ends of the group serve as Overlapping Agents who can trade with the adjacent group. Trades across groups made by the Overlapping Agents have the same search costs as trades within the group. The Small-world Network has the same attributes as the Local Connected Network except that the Small-world Network has Crossover Agents who can pair with an agent in a distant group. Trades made by Crossover Agents have the same search costs as trades made within the group. The bottom right panel in Figure 4.3 shows a crossover in a dashed line, which connects two Crossover Agents. In the real world, Crossover Agents can be considered as middle-men between noncontiguous trade groups such as distant nations.

As in the KW model, artificial agents will pair and make a decision to trade during a round. A collection of rounds makes up a game. Using a random number generator and the discount rate 0.9, each game will end with a 0.1 percent chance. To find out how the number of rounds influences the strategy profile, I vary the number of rounds from 100 to 1200. If the total number of rounds reaches the predetermined endpoint in a game, that game will be the last one of the session. A total of five sessions is used.

There are two initialization schemes I can use to assign which goods are in storage at the beginning of the game. I can either assign a production good or the other non-consumption good according to the unique steady state distribution of goods in storage at the beginning of the game. In general, the initialization scheme is usually as important as the learning algorithm for the equilibrium strategy. However, previous research by Duffy (1999) shows the initialization schemes do not influence the results in the agent-based computer models, inspired by the KW model. I will assign the production good in storage at the start of each game. In the first trade round of a game, the agent has a 50 percent chance to choose either a fundamental or a speculative strategy. After the first round of the game, each agent will use its past experience to determine its future trading strategy by using the learning algorithm. The detailed process is described in the "Learning Algorithm" section, and Figure 4.4 visualizes the whole process in a flow chart.

The learning algorithm

Unlike Kiyotaki and Wright (1989), I assume the agents start interacting without equilibrium beliefs. In the agent-based computer model, the artificial agents learn to adopt optimal trading strategies over time by using a modified version of the learning algorithm built by Duffy (2001). Duffy's learning algorithm is based on findings from Duffy and Ochs' human-subject experiment (1999). With the modified version of the learning algorithm, I can compare the results between using artificial agents and using real agents, as well as compare my findings with Duffy's findings.

There are three cases that each agent can face in a trade round. First, no matter what Type i holds in storage, the agent will offer to trade for Good i because it is the best response. Second, if Type i faces an agent with the same goods, they will not engage in trade. Third, it is more complicated if Type i with Good $i + 1$ has to make a decision to trade for Good $i + 2$, and vice versa. Because Type i immediately consumes Good i and produces Good $i + 1$, Type i can either hold Good $i + 1$ or Good $i + 2$ in storage.

As in Duffy's agent-based computer model (2001, pp. 303-306), I use utility gains and opportunity costs to find out the probability of the Type i offering to trade Good $i + 1$ for Good $i + 2$ and offering to trade Good $i + 2$ for Good $i + 1$. If Type i stores Good i+1 in current period, the utility gains from trading for Good $i + 1$ successfully next period are defined as $g_{i+1} = -c_{i+1} + \beta u$. On the other hand, if Type i with Good $i + 2$ successfully trades with his consumption good next period, the utility gains are defined as $g_{i+2} = -c_{i+2} + \beta u$. If paired agents with different goods do not trade, utility gains become only the storage cost. The net payoff of an agent with Good $i + 1$ in period T is given by

$$v_{i+1}(t) = \sum_{T=0}^{t-1} IS_{i+1}(T) g_{i+1} - \sum_{T=0}^{t-1} IF_{i+1}(T) g_{i+2}$$

IS and IF are indicators to show whether an agent trades for the consumption good successfully. IS_{i+1} is 1 if the agent with a production good trades successfully for the consumption good, otherwise it becomes 0. IF_{i+1} becomes 1 if the agent with a production good fails to trade for a consumption good, otherwise it becomes 0. The net payoff of an agent with Good $i+2$ in period T is given by

$$v_{i+2}(t) = \sum_{T=0}^{t-1} IS_{i+2}(T) g_{i+2} - \sum_{T=0}^{t-1} IF_{i+2}(T) g_{i+1}$$

IS_{i+2} is 1 if the agent with the other non-consumption good trades successfully for a consumption good, otherwise 0. IF_{i+2} becomes 1 only when an agent with the other non-consumption good trades for a consumption good. To get the probability, we need to know the relative benefit of storing Good $i+1$ over Good $i+2$. The relative benefit of storing a production good over the other non-consumption good is denoted as:

$$X(t) = v_{i+1}(t) - v_{i+2}(t)$$

Using this relative benefit, Duffy (2001) derives the logistic specification for the probability that an agent refuses to trade. It is given by

$$\Pr\,[s(t) = 0] = \frac{e^{X(t)}}{1 + e^{X(t)}}$$

The probability that an agent accepts to trade is derived as, $\Pr\,[s(t) = 1]$ = 1 - $\Pr\,[s(t) = 0]$. The agents will use these probabilities when they face a partner with different goods.

Duffy (2001) does not clearly describe how the probability updates when Type *i* faces Type *j* and they both have the same goods in storage. In the modified version of Duffy's learning algorithm, agents will not update the utility gains and opportunity costs of Type *i*. This may cause different results from Duffy's findings.

Experimental Results

The Base Model

The agent-based computer model is parameterized to achieve a unique strategy vector (1, 1, 0), which is also known as the speculative strategy profile. In other words, Type 1 should adopt the speculative trading strategy and Types 2 and 3 should adopt the fundamental trading strategy. According to Table 4.2, using more rounds in a session helps to achieve the speculative strategy profile. The strategy profile with 400 rounds and 96 agents, (0.94, 1.00, 0.09), is the nearest to the unique strategy vector. Unlike earlier experimental studies on the KW model, Type 1 plays the speculative strategy according to the Nash equilibrium prediction of Kiyotaki and Wright. Using the modified version of the learning algorithm built by Duffy (2001) may have fixed the problems of the earlier experiments implemented by others. On top of that, my results are different from Duffy's findings. Type 1 learns to adopt a speculative strategy much faster than those of Duffy's model. One can assume the results stem from the situation, where different rules are applied with agents paired with partners holding the same goods. When I used around 100 rounds in a session, the behavior of agents was not sensitive to the change in the number of agents. However, with more than 200 rounds in a session, it was apparent that the increase in the number of agents makes all types of agents learn to adopt the unique strategy more. I used 400 rounds in a session with 96 agents as my base model components since an increase in the number of rounds and agents in a session improves the results.

Given the base number of rounds and agents, I examined how the distribution of storage costs across agent types affects the strategy profile to verify the base model. Table 4.3 shows that Type 2 learns to adopt the fundamental trading strategy regardless of the change in storage costs across agent types. On the contrary, the trading strategies of Types 1 and 3 are influenced by the change in storage costs. However, all three types of agents behave according to the Nash equilibrium predictions of the KW Model when the condition, $c_1 < c_2 < c_3$, holds, which suggests that the base model is built correctly for further extensions.

Trade Networks

Using the base model, I integrated Wilhite's trade networks into the KW model. The base model is composed of only one group, called a Global Network. In the Global Network, as shown in Table 4.2, only one group exists around the entire economy, and the strategy profile closely reaches the unique strategy vector (1, 1, 0). Table 4.4 indicates how the strategy profile changes across different types of trade networks with different numbers of groups. For example, using 96 agents in each round, there are 24 agents within one group if there are 4 groups. Likewise, if we use 8 and 16 groups in each round, there are 12 agents and 6 agents within one group, respectively. Thus, an increase in the number of groups decreases the number of agents in each group. Fewer agents in every group leads to a smaller number of agents engaging in actual trade, so this may have disturbed the behavior of agents approaching the global equilibrium. Table 4.4 supports the argument that an increase in the number of groups impedes convergence to the unique strategy vector. In addition, when the Local Connected Network, which has both local and global characteristics, is compared with the Local Disconnected Network, it has a faster rate of convergence to the global equilibrium. It is evident that Overlapping Agents in the Local Connected Network improve the speed of convergence to the unique strategy vector. The Small-world Network and Local Connected Network generate similar strategy profiles, but the Small-world Network gives a closer strategy profile to the unique strategy vector. This is due to the fact that the Small-world Network has more Overlapping Agents, including Crossover Agents.

Table 4.5 displays individual group behavior rather than the aggregate behavior of the whole economy. It shows the variation of strategy profiles across each group in the entire economy. The Local Disconnected Network has the most volatility in strategy profiles across trade groups. Some of Type 1, playing the fundamental trading strategy, is apparent in the Local Disconnected Network when the population is divided into 16 groups. Type 2 does not vary across trade groups in all networks. However, Types 1 and 3 have high variations across trade groups, especially in the Local Disconnected Network. The absence of Overlapping Agents in the Local Disconnected Network may cause each group in the economy to approach its own equilibrium strategy profile. The strategy profiles in the Local Disconnected Network and the Small-world Network do not vary as much as the Local Disconnected Network across each group.

Table 4.6 shows how the number of crossovers affects the strategy profile. A crossover connects two agents in distant trade groups. There seems to be little added trade outcome efficiency from additional crossovers. One reason is that there may be sufficient heterogeneity among agents within each group to make trade across more distant trade groups less necessary. In addition, Overlapping Agents may be able to handle sufficient trade with adjacent groups so that trade with more distant groups is unnecessary. On the other hand, as shown in Table 4.4, Table 4.6 also suggests that a decrease in the number of groups leads to a strategy profile closer to the unique strategy vector. Table 4.7 demonstrates whether using more rounds leads to the unique strategy vector. The results suggest that Type 1 does not change much when more rounds are employed. Even Types 2 and 3 do not approach the global equilibrium over time. However, it is apparent that the number of groups influences the strategy profiles when the number of rounds is the same.

Conclusion

The experimental results show how the change in trade networks influences the emergence of goods as media of exchange. The agent-based computer model allows us to vary the parameter values and modifies the KW model for further extensions. Here are the key findings:

First, unlike other previous studies, the result on the behavior of Type 1 is consistent with the KW model. Many economists have tried to implement the model in experimental settings to figure out whether the model is valid or not. My model, which is based on Duffy's model, is consistent with the KW model due to the change in initialization scheme and the learning algorithm. Type 1 plays the speculative trading strategy according to the KW Nash equilibrium prediction, and it leads to the emergence of multiple goods as media of exchange.

Second, the number of rounds and agents in a trade group has a positive relationship with the unique strategy profile. Also, consistent with the KW model, the distribution of storage costs across agent types does not affect the emergence of a good as a medium of exchange.

Third, different types of trade networks affect the strategy profile, which leads to changes in the emergence of goods as media of exchange. In the Local Disconnected Network, where trade groups do not have interactions, the strategy profile of a trade group approaches its own equilibrium. Most importantly, an increase in the number of groups in the whole population has a negative relationship to the unique strategy vector. Therefore, the strategy profiles of the local trade networks do not approach the global equilibrium as fast as those of the Global Network. However, the strategy profile of the Small-world Network approaches the global equilibrium the fastest among the local networks. The Small-world

Network has both local and global attributes and most closely approximates real world trade network systems. However, according to my data analysis, the crossovers do not affect the emergence of goods as media of exchange.

My findings suggest that the KW model is applicable in not only the Global Network but also in local networks including the Small-world Network. Consistent with the KW model, multiple media of exchange emerge in the Small-world Network. On the other hand, the Local Disconnected Network could lead to no medium of exchange. In other words, there could be a barter economy using no medium of exchange when there is a Local Disconnected Network. One possible extension might be the introduction of fiat money, a good without consumption and production values, into the economy. Other extensions may involve changes in trade networks and learning algorithms. Because this agent-based computer model suggests the KW model is correct and valid, it shows that not only human-subject experiments but also the agent-based computer model can be used to verify hypotheses. It is often difficult to set up human subject economic experiments, so the agent-based model may make future experiments easier to conduct.

Figures and Tables

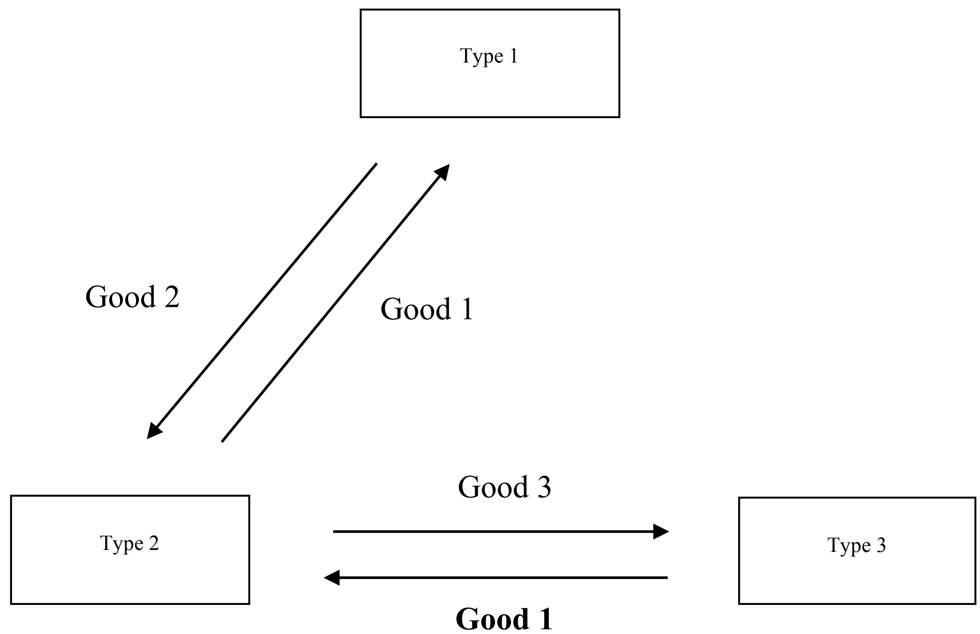

Figure 4.1 Fundamental Equilibrium Exchange Pattern

Note. The medium of exchange is typed in bold.

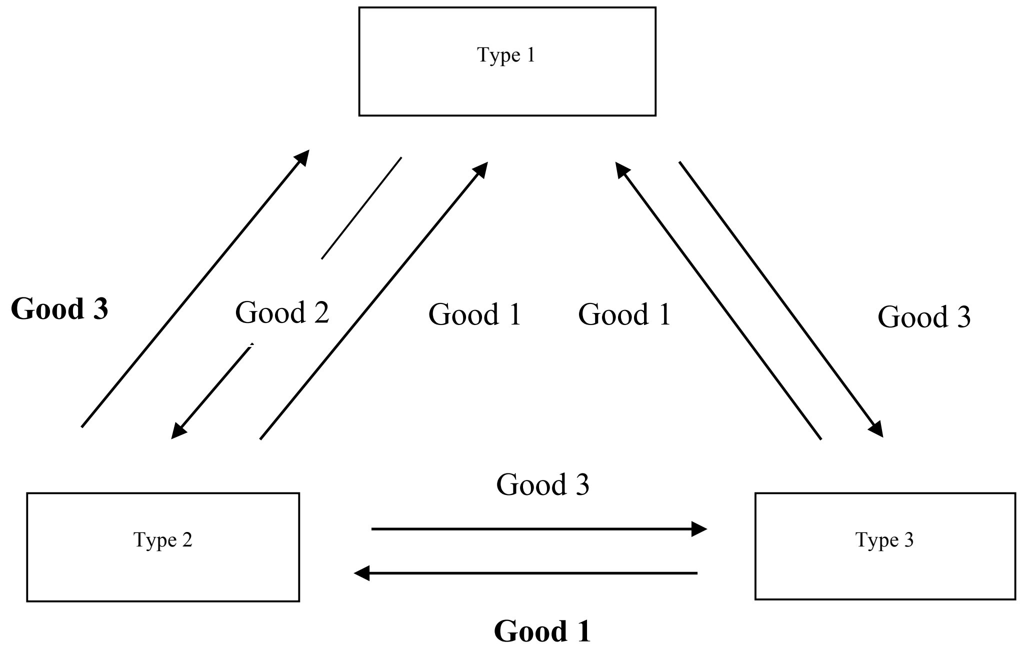

Figure 4.2 Speculative Equilibrium Exchange Pattern

Note. Media of exchange are typed in bold.

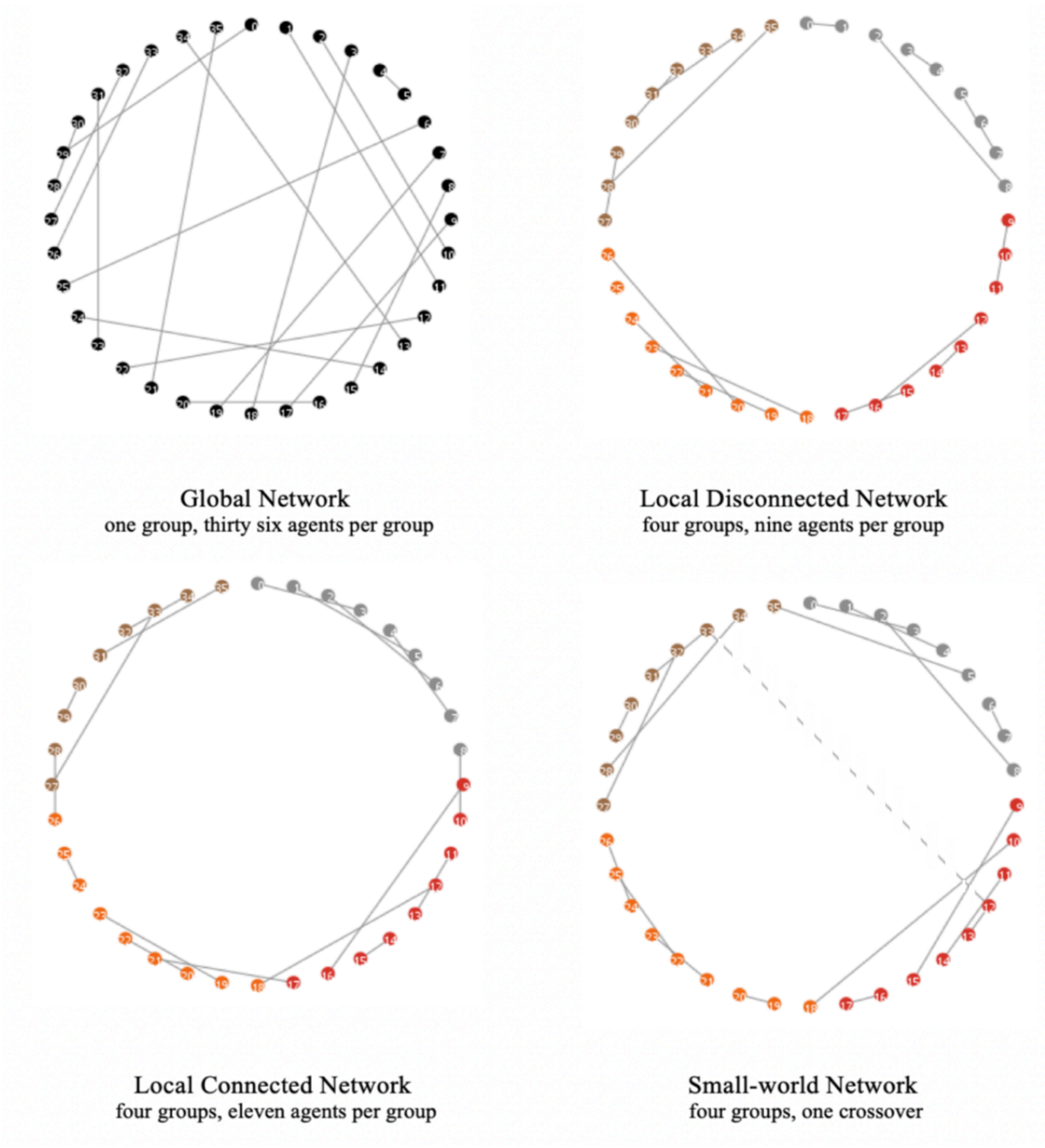

Figure 4.3 Examples of Trade Networks

Note. Different trade groups are displayed in different colors. A solid line between two nods shows paired agents. A dashed line is a crossover, which shows paired Crossover Agents. A crossover connects two Crossover Agents, who are not in contiguous trade groups.

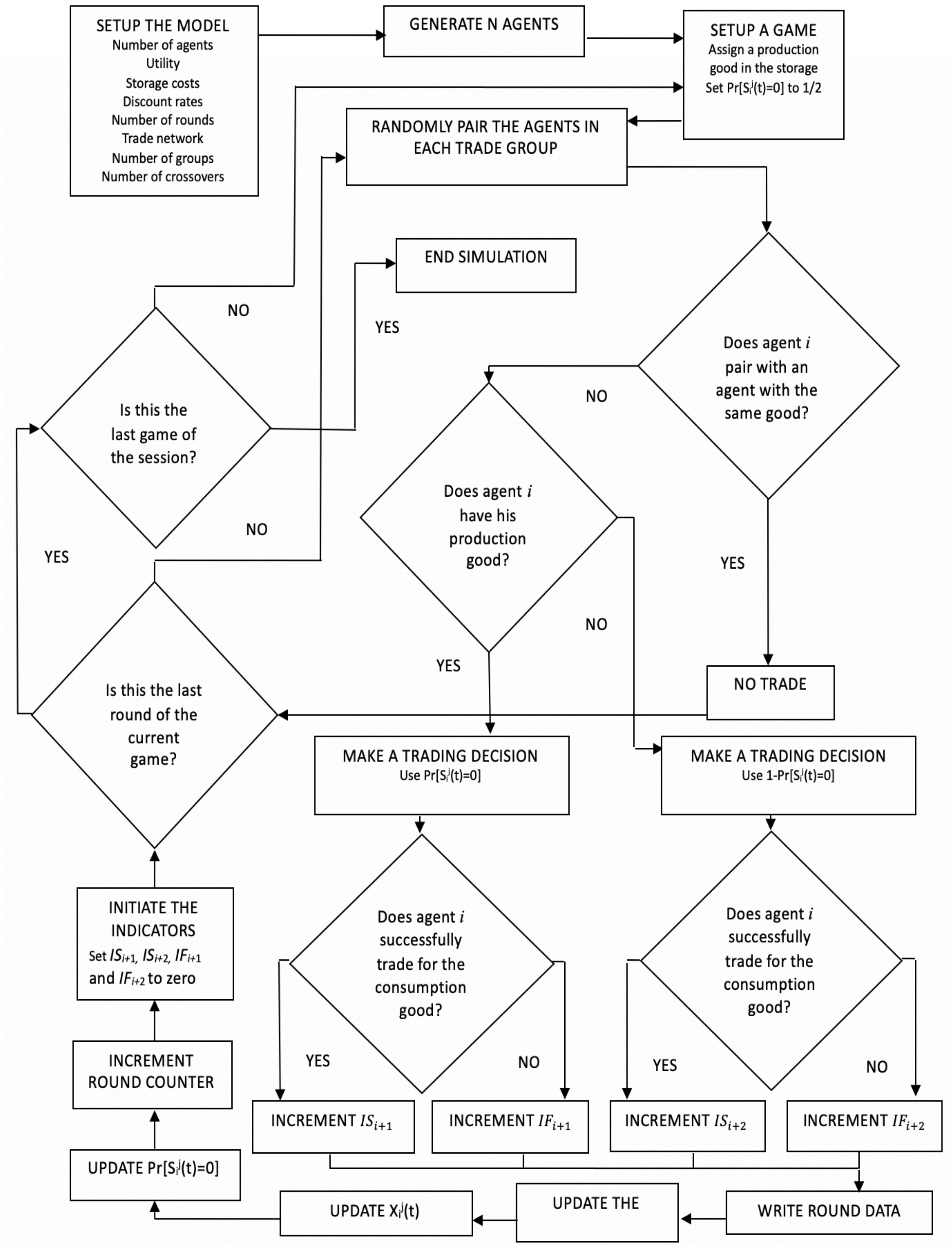

Figure 4.4 Flow of the Simulation

Table 4.1 Model Parameters

Parameters	Values
u	1.00
c_1	0.01 to 0.05
c_2	0.02 to 0.06
c_3	0.05 to 0.09
β	0.90

Table 4.2 The Strategy Profile Across the Three Artificial Agent Types

Number of Agents	Number of Rounds		
	100	200	400
24	(*0.68*, 0.88, 0.47)	(*0.67*, 0.95, 0.40)	(*0.69*, 0.98, 0.30)
48	(*0.64*, 0.87, *0.53*)	(*0.81*, 0.94, 0.31)	(*0.83*, 0.99, 0.19)
72	(*0.67*, 0.91, 0.48)	(*0.80*, 0.96, 0.31)	(*0.91*, 0.99, 0.13)
96	(*0.66*, 0.89, <u>0.50</u>)	(*0.82*, 0.97, 0.28)	(*0.94*, 1.00, 0.09)

Note. Averages calculated from 100 simulated sessions are displayed. An italicized number represents a speculative trading strategy, an ordinary number represents a fundamental trading strategy, and an underlined number represents an indifferent behavior of choosing trading strategies.

Table 4.3 The Strategy Profile Using Different Combinations of Storage Costs

Storage Cost of Good 3	Storage Cost of Good 2				
	C2=0.02	C2=0.03	C2=0.04	C2=0.05	C2=0.06
C1=0.01					
C3=0.05	**(*0.71*, 0.96, 0.35)**	**(*0.91*, 0.96, 0.19)**	**(*0.91*, 0.92 ,0.20)**	(*0.95*, 0.91, 0.18)	(*0.99*, 0.89, 0.16)
C3=0.06	**(*0.85*, 0.98, 0.21)**	**(*0.88*, 0.97, 0.19)**	**(*0.92*, 0.93 ,0.18)**	**(*0.98*, 0.94 ,0.12)**	(*0.98*, 0.93, 0.13)
C3=0.07	**(*0.78*, 0.99, 0.26)**	**(*0.88*, 0.99, 0.17)**	**(*0.92*, 0.98 ,0.13)**	**(*0.95*, 0.98 ,0.10)**	**(*0.98*, 0.95, 0.10)**
C3=0.08	**(*0.74*, 1.00, 0.28)**	**(*0.88*, 0.99, 0.16)**	**(*0.97*, 0.99 ,0.08)**	**(*0.99*, 0.99 ,0.06)**	**(*0.97*, 0.99, 0.07)**
C3=0.09	**(*0.80*, 1.00, 0.23)**	**(*0.87*, 1.00, 0.16)**	**(*0.90*, 0.99 ,0.13)**	**(*0.97*, 1.00 ,0.07)**	**(*0.97*, 1.00 ,0.07)**
C1=0.02					
C3=0.05	(*0.70*, 0.93, 0.40)	**(*0.76*, 0.89, 0.39)**	**(*0.82*, 0.89, 0.33)**	(*0.90*, 0.81, 0.33)	(*0.95*, 0.81, 0.27)
C3=0.06	(*0.69*, 0.98, 0.36)	**(*0.76*, 0.96, 0.31)**	**(*0.85*, 0.91, 0.27)**	**(*0.95*, 0.91, 0.18)**	(*0.97*, 0.90, 0.16)
C3=0.07	(*0.61*, 0.98, 0.42)	**(*0.78*, 0.98, 0.27)**	**(*0.92*, 0.96, 0.17)**	**(*0.91*, 0.98, 0.15)**	**(*0.96*, 0.98, 0.10)**
C3=0.08	(*0.61*, 0.99, 0.41)	**(*0.76*, 0.99, 0.27)**	**(*0.87*, 0.99, 0.17)**	**(*0.92*, 0.99, 0.13)**	**(*0.98*, 0.97, 0.08)**
C3=0.09	(*0.59*, 1.00, 0.42)	**(*0.66*, 1.00, 0.35)**	**(*0.89*, 0.99, 0.15)**	**(*0.97*, 0.99, 0.08)**	**(*0.97*, 0.99, 0.07)**
C1=0.03					
C3=0.05	(*0.60*, 0.92, *0.52*)	(*0.60*, 0.88, *0.56*)	**(*0.88*, 0.81, 0.36)**	(*0.85*, 0.77, 0.43)	(*0.91*, 0.73, 0.40)
C3=0.06	(*0.52*, 0.96, *0.54*)	(*0.69*, 0.92, *0.43*)	**(*0.76*, 0.90, 0.39)**	**(*0.86*, 0.84, 0.34)**	(*0.93*, 0.88, 0.24)
C3=0.07	(*0.52*, 0.97, *0.53*)	(*0.59*, 0.96, *0.46*)	**(*0.76*, 0.95, 0.32)**	**(*0.87*, 0.95, 0.21)**	**(*0.94*, 0.91, 0.19)**
C3=0.08	(0.48, 0.99, *0.53*)	(*0.64*, 0.98, *0.40*)	**(*0.78*, 0.97, 0.29)**	**(*0.85*, 0.96, 0.22)**	**(*0.93*, 0.98, 0.13)**
C3=0.09	(*0.51*, 0.99, *0.51*)	(*0.70*, 1.00, *0.33*)	**(*0.69*, 0.99, 0.32)**	**(*0.83*, 0.99, 0.21)**	**(*0.92*, 0.98 ,0.14)**
C1=0.04					
C3=0.05	(0.34, 0.90, *0.80*)	(*0.53*, 0.85, *0.66*)	(*0.62*, 0.85, *0.58*)	(*0.72*, 0.80, *0.53*)	(*0.92*, 0.62, 0.50)
C3=0.06	(0.36, 0.98, *0.69*)	(0.49, 0.94, *0.60*)	(*0.74*, 0.85, *0.46*)	**(*0.77*, 0.82, 0.45)**	(*0.85*, 0.82, 0.38)
C3=0.07	(0.36, 0.96, *0.70*)	(*0.50*, 0.98, *0.55*)	(*0.62*, 0.95, *0.47*)	**(*0.79*, 0.89, 0.38)**	**(*0.91*, 0.84, 0.29)**
C3=0.08	(0.34, 0.99, *0.67*)	(0.49, 0.90, *0.56*)	(*0.66*, 0.97, *0.40*)	**(*0.76*, 0.95, 0.32)**	**(*0.83*, 0.94, 0.27)**
C3=0.09	(0.41, 1.00, *0.60*)	(*0.51*, 0.99, *0.50*)	(*0.67*, 0.98, *0.37*)	**(*0.76*, 0.97, 0.30)**	**(*0.82*, 0.98, 0.24)**
C1=0.05					
C3=0.05	(0.30, 0.93, *0.82*)	(0.43, 0.84, *0.77*)	(*0.54*, 0.79, *0.70*)	(*0.63*, 0.68, *0.75*)	(*0.76*, 0.63, *0.66*)
C3=0.06	(0.27, 0.95, *0.81*)	(0.33, 0.92, *0.79*)	(*0.53*, 0.86, *0.65*)	(*0.60*, 0.83, *0.62*)	(*0.80*, 0.74, *0.51*)
C3=0.07	(0.22, 0.99, *0.81*)	(0.43, 0.96, *0.64*)	(*0.54*, 0.90, *0.60*)	(*0.69*, 0.87, 0.49)	**(*0.80*, 0.87, 0.37)**
C3=0.08	(0.27, 0.99, *0.76*)	(0.37, 0.98, *0.66*)	(0.50, 0.97, *0.55*)	(*0.66*, 0.94, 0.44)	**(*0.65*, 0.93, 0.45)**
C3=0.09	(0.27, 1.00, *0.75*)	(0.34, 0.99, *0.68*)	(0.47, 0.98, *0.58*)	(*0.66*, 0.98, 0.39)	**(*0.77*, 0.97, 0.31)**

Note. The 3-tuple is typed in bold font if the condition, C1<C2<C3, holds. An italicized number represents a speculative trading strategy, an ordinary number represents a fundamental trading strategy, and an underlined number represents an indifferent behavior of choosing trading strategies. Averages calculated from 100 simulated sessions are displayed. Each session is composed of approximately 400 rounds, and 96 artificial agents are used in each round.

Table 4.4 The Strategy Profile Using Different Number of Groups and Trade Networks

Number of Groups	Trade Networks		
	Local Disconnected	Local Connected	Small-world
4	(*0.69*, 0.96, 0.33)	(*0.75*, 0.97, 0.28)	(*0.75*, 0.97, 0.29)
8	(*0.63*, 0.94, 0.38)	(*0.70*, 0.93, 0.36)	(*0.73*, 0.93, 0.34)
16	(*0.54*, 0.85, 0.49)	(*0.63*, 0.84, 0.49)	(*0.65*, 0.85, 0.47)

Note. Averages calculated from 100 simulated sessions are displayed. Each session is composed of approximately 400 rounds, and 96 artificial agents are used in each round. If there are 4 groups, each group consists of 24 agents, and if there are 8 groups, each group consists of 12 agents. For 16 groups, each group consists of 6 agents. Only one crossover is used in the Small-world Network. Crossovers connect two Crossover Agents, who are not in contiguous trade groups. An italicized number represents a speculative trading strategy, and an ordinary number represents a fundamental trading strategy.

Table 4.5 The Strategy Profile Using Different Number of Groups and Trade Networks

Group Numbers	Trade Networks		
	Local Disconnected	Local Connected	Small-world
4 Groups			
1	(*0.70*, 0.95, 0.33)	(*0.76*, 0.96, 0.29)	(*0.71*, 0.99, 0.30)
2	(*0.71*, 0.98, 0.29)	(*0.77*, 0.96, 0.28)	(*0.83*, 0.96, 0.23)
3	(*0.59*, 0.96, 0.42)	(*0.75*, 1.00, 0.26)	(*0.73*, 0.96, 0.31)
4	(*0.77*, 0.94, 0.28)	(*0.71*, 0.98, 0.30)	(*0.72*, 0.97, 0.31)
8 Groups			
1	(*0.59*, 0.92, 0.44)	(*0.66*, 0.93, 0.40)	(*0.77*, 0.89, 0.35)
2	(*0.54*, 0.94, 0.46)	(*0.73*, 0.92, 0.35)	(*0.76*, 0.91, 0.34)
3	(*0.72*, 0.97, 0.27)	(*0.65*, 0.97, 0.37)	(*0.74*, 0.96, 0.31)
4	(*0.68*, 0.94, 0.34)	(*0.73*, 0.90, 0.36)	(*0.73*, 0.91, 0.34)
5	(*0.64*, 0.94, 0.36)	(*0.73*, 0.92, 0.35)	(*0.68*, 0.93, 0.38)
6	(*0.59*, 0.90, 0.45)	(*0.75*, 0.94, 0.31)	(*0.69*, 0.93, 0.38)
7	(*0.65*, 0.95, 0.35)	(*0.73*, 0.92, 0.35)	(*0.74*, 0.94, 0.32)
8	(*0.64*, 0.95, 0.36)	(*0.67*, 0.90, 0.41)	(*0.75*, 0.94, 0.32)
16 Groups			
1	(*0.63*, 0.80, 0.45)	(*0.63*, 0.89, 0.46)	(*0.70*, 0.83, 0.45)
2	(*0.59*, 0.80, 0.50)	(*0.65*, 0.81, 0.50)	(*0.68*, 0.88, 0.44)
3	(*0.58*, 0.83, 0.46)	(*0.64*, 0.80, *0.54*)	(*0.63*, 0.87, 0.47)
4	(*0.55*, 0.86, 0.49)	(*0.63*, 0.76, *0.56*)	(*0.63*, 0.91, 0.45)
5	(*0.50*, 0.93, 0.46)	(*0.62*, 0.83, *0.52*)	(*0.61*, 0.85, 0.48)
6	(*0.56*, 0.85, 0.47)	(*0.66*, 0.85, 0.46)	(*0.66*, 0.88, 0.44)
7	(*0.52*, 0.89, 0.46)	(*0.64*, 0.90, 0.44)	(*0.68*, 0.83, 0.47)
8	(*0.56*, 0.89, 0.43)	(*0.63*, 0.86, 0.46)	(*0.64*, 0.80, 0.53)
9	(0.48, 0.87, *0.56*)	(*0.61*, 0.86, 0.47)	(*0.52*, 0.82, 0.58)
10	(*0.51*, 0.87, *0.51*)	(*0.60*, 0.87, 0.49)	(*0.54*, 0.92, 0.50)
11	(*0.59*, 0.82, 0.47)	(*0.59*, 0.83, *0.53*)	(*0.60*, 0.87, 0.50)
12	(*0.58*, 0.88, 0.44)	(*0.56*, 0.87, *0.53*)	(*0.68*, 0.80, 0.49)
13	(0.49, 0.85, *0.54*)	(*0.67*, 0.82, 0.47)	(*0.72*, 0.84, 0.45)
14	(0.49, 0.86, *0.53*)	(*0.71*, 0.84, 0.43)	(*0.70*, 0.83, 0.44)
15	(*0.57*, 0.79, *0.52*)	(*0.65*, 0.83, 0.48)	(*0.69*, 0.85, 0.43)
16	(0.50, 0.81, *0.56*)	(*0.66*, 0.82, 0.47)	(*0.68*, 0.87, 0.42)

Note. Averages calculated from 100 simulated sessions are displayed. Each session is composed of approximately 400 rounds, and 96 artificial agents are used in each round. If there are 4 groups, each group consists of 24 agents, and if there are 8 groups, each group consists of 12 agents. For 16 groups, each group consists of 6 agents. Only one crossover is used in the Small-world Network. An italicized number represents a speculative trading strategy, an ordinary number represents a fundamental trading strategy, and an underlined number represents an indifferent behavior of choosing trading strategies.

Table 4.6 The Strategy Profile Using Various Number of Crossovers

Number of Crossovers	Number of Groups: 8	12	16
1	(*0.73*, 0.93, 0.34)	(*0.65*, 0.93, 0.41)	(*0.65*, 0.85, 0.47)
2	(*0.74*, 0.93, 0.33)	(*0.62*, 0.94, 0.41)	(*0.61*, 0.87, 0.49)
3	(*0.68*, 0.92, 0.39)	(*0.64*, 0.92, 0.41)	(*0.63*, 0.86, 0.47)

Note. Averages calculated from 100 simulated sessions are displayed. Each session is composed of approximately 400 rounds, and 96 artificial agents are used in each round. Crossovers connect two Crossover Agents, who are not in contiguous trade groups. An italicized number represents a speculative trading strategy, and an ordinary number represents a fundamental trading strategy.

Table 4.7 The Strategy Profile Using Various Number of Rounds

Number of Rounds	Number of Groups		
	4	8	16
Local Disconnected			
400	(*0.69*, 0.96, 0.33)	(*0.63*, 0.94, 0.38)	(*0.54*, 0.85, 0.49)
800	(*0.70*, 0.96, 0.28)	(*0.58*, 0.92, 0.41)	(*0.53*, 0.88, 0.45)
1200	(*0.69*, 0.97, 0.27)	(*0.63*, 0.92, 0.36)	(*0.54*, 0.85, 0.46)
Local Connected			
400	(*0.75*, 0.97, 0.28)	(*0.70*, 0.93, 0.36)	(*0.63*, 0.84, 0.49)
800	(*0.79*, 0.98, 0.21)	(*0.76*, 0.93, 0.29)	(*0.64*, 0.85, 0.46)
1200	(*0.79*, 0.97, 0.21)	(*0.70*, 0.96, 0.31)	(*0.66*, 0.87, 0.43)
Small-world			
400	(*0.75*, 0.97, 0.29)	(*0.73*, 0.93, 0.34)	(*0.65*, 0.85, 0.47)
800	(*0.83*, 0.98, 0.19)	(*0.73*, 0.92, 0.33)	(*0.60*, 0.87, 0.48)
1200	(*0.80*, 0.98, 0.20)	(*0.75*, 0.93, 0.29)	(*0.62*, 0.89, 0.44)

Note. Averages calculated from 100 simulated sessions are displayed. Each session is composed of approximately 400, 800 or 1200 rounds, respectively, and 96 artificial agents are used in each round. If there are 4 groups, each group consists of 24 agents, and if there are 8 groups, each group consists of 12 agents. For 16 groups, each group consists of 6 agents. Only one crossover is used in the Small-world Network. Crossovers connect two Crossover Agents who are not in contiguous trade groups. An italicized number represents a speculative trading strategy, and an ordinary number represents a fundamental trading strategy.

CHAPTER 5. CONCLUSION

This dissertation finds how the financial side of a firm matters to employment levels, how a contrast stimulus affects the risk attitudes of individuals, and how networks influence the emergence of the medium of exchange, respectively in each chapter. Although these chapters focus on somewhat distinct areas, each chapter deals with emerging non-trivial issues in financial and monetary economics.

To begin, Chapter 2 shows cash holdings are critical to maintain stable employment levels in response to consumer demand shocks. These effects are amplified for financially constrained firms like small firms and firms in the high-tech sector. This chapter provides empirical evidence that firm balance sheets matter to employment levels. Unlike previous studies on the role of indebted households and financial intermediaries, the result of this chapter strengthens employment policies that target firms directly.

Following, Chapter 3 implements an experiment and finds that individuals exposed to a positive stimulus behave more risk-seeking in investment decisions. However, it is intriguing that the stimulus does not impact individuals when they make financing decisions. Participants in the experiment spent more time and changed their answers more often when making financing decisions compared to making investment decisions. This result can imply financing decisions would require more mental effort due to less familiarity.

Finally, Chapter 4 illustrates how trade networks influence the emergence of goods as media of exchange. This chapter shows that agents can adopt speculative trading strategies, which can lead to the emergence of multiple media of exchange. Also, different types of trade networks can change types of media of exchange. I consider only commodity money, so the introduction of fiat money can be one possible extension for my future research.

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