경영학박사학위논문

Essays on the Financial and Labor Markets

주식시장과 노동시장에 관한 연구

2015 년 8 월

서울대학교 대학원

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이 논문을 경영학 박사 학위논문으로 제출함

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Abstract

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This thesis consists of two essays on the financial and labor market. The first chapter studies how the elasticity of intertemporal substitution (EIS) influences labor market fluctuations in the labor search and matching model with both extensive and intensive margins of labor supply. With the curvature of utility, the countercyclical marginal utility of consumption induces the flow value of unemployment to be procyclical, and the stock returns to be countercyclical. The former effect reduces unemployment volatility by weakening wage rigidity. In contrast, the latter effect magnifies unemployment volatility by discounting higher future payoffs from hiring at a lower discount rate, if wages do not absorb all of productivity shocks. The higher EIS reduces the procyclicality of the flow value of unemployment, and reinforces the countercyclicality of the stock returns. We quantitatively show that a high level of the EIS is required to resolve the unemployment volatility puzzle.

The second chapter investigates why the positive momentum profit does not exist in the Korean stock market by examining how stock prices respond to public news. Even though the entire set of stocks does not show positive post holding period returns, stocks with news headlines have significantly positive momentum profits, which are mainly driven by return drifts of bad performers with news. However, good performers with public news, as well as those without news, present return reversal in Korea, which is opposite to the case of the U.S.(see Chan (2003)). This difference explains the absence of momentum in Korea. The asymmetric reaction of stock price to news is ignored by major theories on the momentum. Further analyses indicate that transactional frictions can be more plausible explanation for this phenomenon than the incentive of managers to disclose bad news slowly.

Keywords: Elasticity of Intertemporal Substitution; Unemployment Volatility; Momentum; Public News

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Chapter 1

Flow Value of Unemployment, Stock Returns, and Unemployment Volatility

1.1 Introduction

The labor search and matching model of Mortensen and Pissarides (1994) (MP model hereafter) has become the standard workhorse of equilibrium unemployment. However, Shimer (2005) argues that the standard calibration of the MP model is unable to reproduce the volatility of unemployment and vacancies observed in the postwar U.S. data. The quantitative failure of the MP model is attributed to the way wages are determined: the Nash-bargained wages respond strongly to variations in productivity. Therefore, the literature has proposed numerous modifications of the MP model that generate wage rigidity, among which the small surplus calibration of Hagedorn and Manovskii (2008) and the alternating-offer wage bargaining of Hall and Milgrom (2008) are the leading solutions to the unemployment volatility puzzle.

There are considerable debates about empirical plausibility of those alternative models. However, the literature has commonly adopted the strong assumption of the MP model: utility is linear. The absent of curvature in utility has been regarded to be an appropriate approximation to the richer MP model, not only because productivity changes are relatively small and not permanent, but also because the log-linearization is typically used to quantify the cyclical properties of the MP model. The goal of this paper is to relax the assumption of linear utility and to analyze the relationship between the elasticity of intertemporal substitution

(EIS hereafter) and unemployment volatility in the MP model. Using the non-linear solutions, we suggest that the magnitude of the willingness to trade-off consumption over time plays a key role in determining the success of the MP model to account for labor market fluctuations.

We embed the MP model with the alternating-offer wage bargaining into a dynamic stochastic general equilibrium model with the preference of both extensive and intensive margins of labor supply used by Hall and Milgrom (2008). We find that the curvature of utility influences unemployment volatility via two offsetting channels: the wage channel and the discount rate channel.

The wage channel represents that the curvature of utility affects wage rigidity through the procyclicality of the flow value of unemployment. According to Hall and Milgrom (2008), the flow value of unemployment[1] is made up of unemployment benefits and the flow value of non-working time in terms of consumption. The second measures the additional value that the household gains by shifting a worker from employment to unemployment, which equals the sum of increase in flow utility and decrease in consumption of the worker moving from work to nonwork. With the linear utility, the flow value of unemployment is regarded to be constant. This assumption plays an important role in generating wage rigidity in

[1]This terminology is from Hall (2014). Hall and Milgrom (2008) and Chodorow-Reich and Karabarbounis (2014) use “the flow value of nonwork” and “the opportunity costs of employment” instead, respectively.

many models including the alternating-offer wage bargaining. With the curvature of utility, the countercyclical marginal utility of consumption induces the flow value of non-working time to rise in response to positive productivity shocks. In other words, the household appreciates the contribution of the unemployed more than that of the employed during booms, when the marginal utility of consumption is low due to larger consumption. If unemployment benefits are relatively small, the flow value of unemployment in total becomes procyclical, weakening wage rigidity generated by the alternating-offer wage bargaining. Therefore, the wage channel of the curvature in utility reduces labor market fluctuations. This intuition is suggested by Pissarides (1985), and Hagedorn and Manovskii (2008). More recently, Chodorow-Reich and Karabarbounis (2014) empirically show that the procyclicality of the flow value of unemployment is able to dampen the ability of the MP model to replicate business cycle facts, which is against the common view of the search literature.

The discount rate channel represents that the curvature of utility influences discount rates through the stochastic discount factor. Whereas the linear utility implies constant discount rates, the curvature of utility gives rise to countercyclical discount rates. If the equilibrium wage does not soak up all of productivity shocks, the stock price rises in response to increase of productivity, discounting higher future profits at a lower discount rate. As the decline of stock returns raises the expected payoffs from hiring a new worker, the firm tends to invest more resources in recruitment. Therefore, the discount rate channel of the curvature in utility magnifies labor market fluctuations. Mukoyama (2009) also suggests that the labor market volatility is amplified by the exogenously procyclical discount factor, which can be interpreted by a cyclical stochastic discount factor.

The total effect of two offsetting channels on unemployment volatility crucially depends on the magnitude of the EIS. When the EIS is low, the household is more reluctant to change consumption over time. Also hours worked, which are complements to consumption, become countercyclical due to the strong wealth effect.[2] These strengthen the countercyclicality of the marginal utility of consumption that is decreasing in consumption and increasing in hours worked. The household, therefore, tends more to depreciate the relative value of consumption from wage incomes to non-working time during expansions. As a result, the flow value of unemployment gets more procyclical, which undermines wage rigidity. On the other hand, the large wealth effect discourages the agents from taking advantage of the temporal increase in labor productivity by opening more vacancies. Furthermore, more flexible wages reduce variations in firm's profits, and thus suppress fluctuations in stock returns. Therefore, the stronger desire for

[2]Note the complementarity between consumption and hours does not mean that consumption and hours worked move synchronously in the MP model, where wages and hours are bargained.

consumption smoothing lowers labor market fluctuations. When the EIS is high, larger changes in consumption are acceptable, and hours worked become procyclical due to the strong substitution effect. The marginal utility of consumption, therefore, gets less countercyclical. This induces the flow value of unemployment to be less procyclical. Moreover, more productivity-insulated wages reinforce the coutercyclicality of stock returns. Because the substitution effect dominates the wealth effect, the discount rate effect amplifies the incentive to save for the future and invest in hiring. Therefore, the weaker desire for consumption smoothing enlarges labor market fluctuations.

In the quantitative analysis, the MP model with the alternating-offer wage bargaining is able to replicate the observed labor market moments under the EIS parameter of 2.0. At the same time, we obtain high volatility of stock returns and low volatility of risk-free rates comparable to the data, which represents the link between financial market volatility and labor market volatility. Meanwhile, the MP model with the Nash wage bargaining also shows the same relationship between the EIS and unemployment volatility under the standard calibration and under the small surplus calibration of Hagedorn and Manovskii (2008). But it presents much weaker labor market fluctuations. The alternating-offer-bargained wages depend mainly on the disagreement payoffs that are affected not only by the flow value of unemployment but also by the bargaining delay costs and the bargaining termination probability. In contrast, the Nash-bargained wages rely on the outside option payoffs that are influenced only by the flow value of unemployment. Thus, the procyclical flow value of unemployment causes the Nash-bargained wages to be more responsive to changes of productivity even under the small surplus calibration.

There is little agreement in the macroeconomics and finance literature about the appropriate magnitude of the EIS. Hall (1988) and Campbell (1999) argue that the EIS is close to zero. On the contrary, Attanasio and Vissing-Jorgensen (2003), Gruber (2006), and van Binsbergen, Fernández-Villaverde, Koijen, and Rubio-Ramírez (2012) claim that the EIS is well over one. Also, Bansal and Yaron (2004), Gourio (2012), and Nakamura, Steinsson, Barro, and Ursúa (2013) find that the low EIS entails counter-factual implications for busyness cycles and asset prices in their models. In our model, the EIS parameter of 2.0 generates the EIS estimate close to zero in the regression of Hall (1988), which confirms the downward bias of the estimation approach. In addition, the low EIS counterfactually involves the countercyclical hours worked and the negative autocorrelation of dividends, because of the strong wealth effect. These results motivate the high level of the EIS in our model.

This paper is built on two strands of the literature. The first group tries to resolve the unemployment volatility puzzle of Shimer (2005) by improving the MP model and by verifying quantitative and empirical plausibility of the modifications. Chodorow-Reich and Karabarbounis (2014) structurally measure the flow value of unemployment derived by Hall and Milgrom (2008) using the microdata and the administrative data. They find that the flow value of unemployment is estimated to be so procyclical that an elasticity of the flow value of unemployment with respect to the marginal product of employment is close to one. As a consequence, they argue that the unemployment volatility puzzle cannot be resolved by the wage rigidity that appeals to the assumption that the flow value of unemployment is constant as in Hagedorn and Manovskii (2008) and Hall and Milgrom (2008). Our paper complements Chodorow-Reich and Karabarbounis (2014) in the following ways. First, we analyze how the EIS changes the procyclicality of the flow value of unemployment. For the purpose, we use the utility specification suggested by Hall and Milgrom (2008), which allows us to choose values of the EIS parameter flexibly. On the contrary, the utility form used by Chodorow-Reich and Karabarbounis (2014) requires only low values of the EIS parameter for obtaining the complementarity between consumption and hours worked at the same time. Second, we more rigorously analyze the effect of the procyclical flow value of unemployment on wage rigidity and unemployment volatility, using the non-linear solutions. Third, we argue that the countercyclical marginal utility of consumption influences labor market fluctuations not only through the flow value of unemployment, but also through the discount rates. Meanwhile, Hall (2014), and Albertini and Poirier (2014) show that countercyclical discount rates are able to drive up unemployment volatility. From the view point that labor productivity is not a good driving force in the MP model because of the observed low correlation between productivity and unemployment, they assume that discount rates move exogenously independent of productivity . In contrast, the stochastic discount factor in our model endogenously fluctuates in response to changes in the marginal utility of consumption.

The second group tries to account for the business cycles by introducing the search and matching frictions in the labor market into the real business cycle model, which is pioneered by Merz (1995) and Andolfatto (1996). Petrosky-Nadeau, Zhang, and Kuehn (2013) present that the labor market frictions replicate financial market moments, such as high equity premiums, high volatility of stock prices, and low and stable risk-free rates. They argue that the fixed component in the vacancy-posting costs and the small surplus calibration similar to Hagedorn and Manovskii (2008) give rise to economic disasters inside the model. Although our paper focuses on the labor market moments, both papers emphasize the link between the labor market and the financial market in the context of the real business cycle model. Because the procyclical flow value of unemployment may hamper the endogenous disaster mechanism, the results of our paper also bear on Petrosky-Nadeau, Zhang, and Kuehn (2013).

The paper proceeds as follows. Section 1.2 presents the economy. Section 1.3 parameterizes the model. Section 1.4 studies the quantitative results. Section 2.7 discusses some extensions and robustness. Section 1.6 concludes. The supplemental technical appendix provides the derivations of all equations, the data sources, and the computational algorithm.

1.2 Model

We embed the standard labor market search and matching frictions of Mortensen and Pissarides (1994) into a dynamic stochastic general equilibrium model with both extensive and intensive margins of labor supply. Time is discrete and infinite. Consumption is the numeraire good. The economy is populated by a representative firm and a representative household family. The firm is owned by the household, produces output with labor, and pays out profits as dividends. The household family is made up of a continuum of identical workers of mass one. And it perfectly insures its members against personal income variations, achieving equal marginal utility across all workers. The perfect insurance assumption is widely used for analytical simplicity in the literature.[3] Without this assumption, we should track an individual state variable, wealth, of all employed and unemployed workers for aggregation. Although some studies, such as Blundell, Pistaferri, and Preston (2008), show that individual

[3] Merz (1995), Andolfatto (1996), Hall (2009), Eusepi and Preston (2014), Chodorow-Reich and Karabarbounis (2014), etc.

workers are substantially insured against transitory income risks, we view the perfect insurance assumption as a convenient approximation to the reality that permits the tractability of the representative agent approach as in Hall (2009).

1.2.1 Search and Matching Frictions in the Labor Market

In each period t, a fraction n_t of workers are employed and producing output. A remaining fraction $u_t = 1 - n_t$ of workers are unemployed and searching for a job. For simplicity, we ignore small cyclical variations in labor force participation. At the beginning of period t, the firm posts job vacancies v_t to increase next-period employment n_{t+1}. Holding a vacancy open costs κ_t per unit of time. We assume that κ_t is constant at κ in the baseline model.

The flow of successful matches m_t is determined by a constant-return-to-scale matching function $m(u_t, v_t)$, which is increasing and strictly concave in u_t and v_t. The matching function represents labor market frictions, such as lack of coordination, imperfect information, and heterogeneity of vacancies and workers. Although all family members are allocated to working, only a fraction of them become employed and the remainder are searching for a job. For the matching function, we adopt the functional form introduced by den Haan, Ramey, and Watson (2000).[4]

$$m(u_t, v_t) = \frac{u_t v_t}{(u_t^\iota + v_t^\iota)^{1/\iota}}, \quad \iota > 0 \tag{1.1}$$

Let θ_t denote the vacancies/unemployment ratio (v_t/u_t), which represents labor market tightness from firm's perspective. From the matching function (1.1), the vacancy-filling rate q_t of the firm and the job-finding rate f_t of workers are given by

$$q_t = q(\theta_t) = \frac{m_t}{v_t} = \frac{1}{(1+\theta_t^\iota)^{1/\iota}} \tag{1.2}$$

$$f_t = f(\theta_t) = \frac{m_t}{u_t} = \frac{1}{(1+\theta_t^{-\iota})^{1/\iota}} = \theta_t q_t \tag{1.3}$$

As the labor market becomes tighter, it is more difficult for the firm to recruit a worker ($q'(\theta_t) < 0$), but it is easier for job-seekers to become employed ($f'(\theta_t) > 0$). q_t and f_t are outcomes from an interaction between the workers and the firm in the labor market. However, the household and the firm take them as a given feature of the labor market.

At the beginning of next period $t+1$, matched workers and the firm haggle over hours worked h_{t+1} and a wage rate w_{t+1}. Both have some bargaining power, because the matching frictions prevent vacancies or workers from being replaced instantaneously. We will describes determination of

[4]Unlike the standard Cobb-Douglas specification, this functional form ensures that the vacancy-filling rate and the job-finding rate lie between zero and one for all u_t and v_t. This feature is important because our calibration strategy targets the observed average of θ_t.

hours worked and a wage rate in Section 1.2.4. Employed workers exogenously lose their job with a separation rate ϕ.[5] Therefore, employment evolves as follows.

$$n_{t+1} = (1-\phi)n_t + q_t v_t \tag{1.4}$$

1.2.2 Household's Decisions

Taking the labor market outcomes and the path of prices as given, the household family maximizes utility by choosing consumptions of employed and unemployed workers, $c_{n,t}$ and $c_{u,t}$.

$$J_t = \max_{c_{n,t}, c_{u,t}} n_t U_t(c_{n,t}, h_t) + u_t U_t(c_{u,t}, 0) + \beta \mathbb{E}_t \left[J_{t+1} \right] \tag{1.5}$$

where β is the discount factor, and $\mathbb{E}_t$ is the mathematical expectation conditional on the information set at period t. $U_t(c_t, h_t)$ is a period utility that is assumed to be the specification of Hall and Milgrom (2008).[6]

$$U_t(c_t, h_t) = \frac{c_t^{1-1/\psi}}{1-1/\psi} - \tau c_t^{1-1/\psi} h_t^{1+1/\chi} - \varphi \frac{h_t^{1+1/\chi}}{1+1/\chi} + Q \tag{1.6}$$

[5] Shimer (2005) shows that most unemployment volatility is explained by fluctuations in job creation, rather than in job destruction.

[6] The utility specifications of Greenwood, Hercowitz, and Huffman (1988), such as our utility, are not consistent with a balanced growth path, causing a long-run growth in hours worked in the model with an aggregate trend. To remedy this problem, many attach the aggregate trend to the term of the disutility from hours worked in the utility function (Campbell and Ludvigson, 2001; Rudebusch and Swanson, 2012). Meanwhile, we fail to have both high values of the EIS parameter and the complementarity in the utility forms of King, Plosser, and Rebelo (1988) that are the generalized version of the one used by Chodorow-Reich and Karabarbounis (2014).

where c_t is consumption and h_t is hours worked. ψ controls the elasticity of intertemporal substitution (EIS)[7], and τ sets the complementarity between consumption and hours worked. ψ and τ should satisfy an inequality of $\tau(1-\psi) > 0$ to make the household assign a higher level of consumption to employed workers than to unemployed workers ($U_{ch} > 0$). χ determines the Frisch elasticity of labor supply, and φ governs the disutility of hours worked. Note eliminating the complementarity ($\tau = 0$) from the utility fixes the consumption demand elasticity and the labor supply elasticity at ψ and χ, respectively. Finally, Q parameterizes the additional utility from consuming non-marketed home production. Following Chodorow-Reich and Karabarbounis (2014), we add this parameter to target the level of the flow value of unemployment and thus the unemployment rate. We assume that Q equals a positive constant for the unemployed and zero for the employed.

The budget constraint of the household is

$$n_t c_{n,t} + u_t c_{u,t} + T_t + \frac{b_{t+1}}{R_t^f} + a_{t+1} e_t = w_t h_t n_t + \eta u_t + b_t + a_t(d_t + e_t) \quad (1.7)$$

where η is unemployment benefits per the unemployed, b_t is holdings of risk-free assets, R_t^f is a risk-free rate, a_t is holdings of equity shares, e_t is an ex-dividend equity value, d_t is dividends, and $T_t = \eta u_t$ is lump-sum

[7] If ψ goes to one and τ is redefined, it becomes

$$U_t(c_t, h_t) = \log c_t - \tau h_t^{1+1/\chi} \log c_t - \varphi \frac{h_t^{1+1/\chi}}{1+1/\chi} + Q$$

taxes to finance the public benefits. Let λ_t denote a Lagrange multiplier on the budget constraint. Then a stochastic discount factor M_{t+1} is given by

$$M_{t+1} = \beta \frac{\lambda_{t+1}}{\lambda_t} = \beta \left(\frac{c_{u,t+1}}{c_{u,t}} \right)^{-1/\psi} = \beta \left(\frac{c_{n,t+1}}{c_{n,t}} \right)^{-1/\psi} \left(\frac{1 - \tau(1-1/\psi) h_{t+1}^{1+1/\chi}}{1 - \tau(1-1/\psi) h_t^{1+1/\chi}} \right) \tag{1.8}$$

To save on notations, define $U_t^n = U_t(c_{n,t}, h_t)$ and $U_t^u = U_t(c_{u,t}, 0)$. From the household's problem, the marginal value of an unemployed worker to the household $J_{u,t}$ is given in terms of consumption by

$$\frac{J_{u,t}}{\lambda_t} = \frac{U_t^u}{\lambda_t} - c_{u,t} + \eta + \mathbb{E}_t \left[M_{t+1} \left\{ \frac{J_{n,t+1}}{\lambda_{t+1}} f_t + \frac{J_{u,t+1}}{\lambda_{t+1}} (1 - f_t) \right\} \right] \tag{1.9}$$

An additional unemployed worker provides the household with the sum of period utility, unemployment benefits net of consumption, plus the expected discounted marginal value in next period, in which she finds a job with a probability f_t or stays unemployed with a probability $1 - f_t$. $J_{u,t}$ plays a role of an outside option of the matched worker in wage negotiation. Note the tighter labor market raises $J_{u,t}/\lambda_t$ through the higher job-finding rate. Because the MP model counterfactually shows high contemporaneous correlation between productivity and tightness, $J_{u,t}/\lambda_t$ is also vulnerable to productivity changes. Similarly, the marginal value of an employed worker to the household $J_{n,t}$ is given in terms of consumption by

$$\frac{J_{n,t}}{\lambda_t} = \frac{U_t^n}{\lambda_t} - c_{n,t} + w_t h_t + \mathbb{E}_t \left[M_{t+1} \left\{ \frac{J_{n,t+1}}{\lambda_{t+1}} (1 - \phi) + \frac{J_{u,t+1}}{\lambda_{t+1}} \phi \right\} \right] \tag{1.10}$$

An additional employed worker contributes the sum of period utility, wages net of consumption, plus the expected discounted marginal value in next period, in which she remains employed with a probability $1-\phi$, or loses a job with a probability ϕ. In sum, the household gets the following surplus, when an additional unemployed member becomes employed.

$$\begin{aligned}\frac{J_{n,t}-J_{u,t}}{\lambda_t} &= w_t h_t - \left[\eta - (c_{u,t}-c_{n,t}) + \left(\frac{U_t^u - U_t^n}{\lambda_t}\right)\right] \\ &\quad + (1-\phi-f_t)\mathbb{E}_t\left[M_{t+1}\left\{\frac{J_{n,t+1}-J_{u,t+1}}{\lambda_{t+1}}\right\}\right] \qquad (1.11)\end{aligned}$$

The second bracketed term of (1.11) represents the flow value of unemployment per person denoted by z_t.

$$z_t = \eta + \frac{[U_{u,t}-\lambda_t c_{u,t}] - [U_{n,t}-\lambda_t c_{n,t}]}{\lambda_t} = \eta + \varrho_t \qquad (1.12)$$

Note the flow value of unemployment per hour z_t/h_t is more relevant to our model with the intensive margin of labor supply, because w_t is per unit of hour. In contrast, the flow value of unemployment per person z_t is more related to the model without the intensive margin of labor supply, where w_t is per unit of person.

z_t contains not only the unemployment benefits η, but also the flow value of non-working time in terms of consumption ϱ_t. ϱ_t measures the additional utility that the household gains when a worker quits a job and enjoys non-working time. Chodorow-Reich and Karabarbounis (2014) show that (a) η is countercyclical but takes up only a small portion, and

(b) ϱ_t is highly procyclical. Therefore, the flow value of unemployment in total is procyclical and volatile over the business cycle. When productivity increases, consumption grows and the marginal utility of consumption declines. As a result, the relative value of non-working time to consumption from wage incomes gets higher. In other words, the household appreciates the contribution of an unemployed worker more than that of an employed worker during booms. This causes the flow value of unemployment to be procyclical. Chodorow-Reich and Karabarbounis (2014) also show that cyclical movements in ϱ_t is mainly determined by procyclicality of λ_t.[8] Therefore, the cyclicality of the flow value of unemployment crucially relies on the EIS parameter. If ψ increases, changes in consumption are less costly. Thus, λ_t becomes less countercyclical, and ϱ_t and z_t become less procyclical.

As we note earlier, we add the value of home production Q to target the level of z_t, because η is estimated to be small. However, Q affects z_t in a different way from η. Q is measured in terms of utility, whereas η is in terms of consumption. As z_t contains Q/λ_t in exchange for η, the counter-cyclical of λ_t becomes more influential, increasing the procyclicality of z_t. Chodorow-Reich and Karabarbounis (2014) also show that an elasticity of the flow value of unemployment with respect to the marginal production

[8] From the first order conditions for $c_{n,t}$ and $c_{u,t}$, and the optimal conditions for h_t (1.24), we can express z_t as an implicit function of λ_t, which is the same across employed and unemployed workers.

of employment does not vary much in response to changes in Q, which is in contrast with η.

1.2.3 Production and Firm's Decisions

The firm produces output y_t using labor as its only input according to the following linear production function.

$$y_t = p_t n_t = x_t h_t n_t \tag{1.13}$$

where p_t is the marginal product of employment, and x_t is labor productivity whose log value follows a AR(1) process with a persistence ρ and a normal disturbance ε_t.

$$\log x_t = \rho \log x_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim iid\ N(0, \sigma^2) \tag{1.14}$$

To focus on the labor market and gain computational simplicity, we abstract from physical capital in the production, following the literature.[9] Physical capital shows smooth cyclical variations, and thus has little impact on the marginal product of employment that is considered to be the main driving force for unemployment volatility. However, we believe that adding curvature into the production will be a productive research to generate more realistic payoffs of the firm.

If the firm employs n_t workers and posts v_t vacancies, it receives profits

[9] Shimer (2005), Pissarides (2009), Petrosky-Nadeau, Zhang, and Kuehn (2013), etc.

in period t equal to revenues net of wages and vacancy-posting costs.

$$d_t = y_t - w_t h_t n_t - \kappa_t v_t \tag{1.15}$$

The firm is risk-neutral and discounts future payoffs with the same stochastic discount factor as does the household. Taking the labor market outcomes and the path of prices as given, the firm maximizes cum-dividend value by posting vacancies v_t, subject to the employment evolution condition and the nonnegative vacancy condition.

$$S_t = \max_{v_t} \left\{ d_t + \mathbb{E}_t \Big[M_{t+1} S_{t+1} \Big] \right\} \tag{1.16}$$

$$s.t.$$

$$n_{t+1} = (1 - \phi) n_t + q_t v_t \tag{1.17}$$

$$v_t \geq 0 \tag{1.18}$$

As in Petrosky-Nadeau, Zhang, and Kuehn (2013), we impose the nonnegative vacancy condition (1.18), because it is occasionally binding under some calibrations of the MP model with the Nash-bargained wages. It also facilitates obtaining numerical solutions to the model by preventing the vacancy-filling rate larger than one. However, this constraint is not essential in the model, as it does not bind in simulations based on our calibrations of the Nash wage bargaining model. Also, vacancies are always positive in the alternating-offer wage bargaining model.

Let π_t and $\lambda_t q_t$ denote a Lagrangian multiplier on the employment evolution condition and the nonnegative vacancy condition, respectively.

Then the first order condition for v_t yields the intertemporal job creation condition.

$$\frac{\kappa_t}{q_t} - \zeta_t = \mathbb{E}_t \left[M_{t+1} \left\{ x_{t+1} h_{t+1} - w_{t+1} h_{t+1} + \left(\frac{\kappa_{t+1}}{q_{t+1}} - \zeta_{t+1} \right) (1 - \phi) \right\} \right] \tag{1.19}$$

In the equilibrium, the marginal cost of hiring an additional employee (or filling an additional vacancy) equals the expected discounted profits from the recruitment that equal the sum of the marginal product of employment net of wages, plus savings in the next-period marginal cost of hiring . The Kuhn-Tucker condition from the nonnegative vacancy condition is given by

$$\begin{aligned} v_t = 0,\ \zeta_t q_t > 0 \quad & \text{if binding} \\ v_t > 0,\ \zeta_t q_t = 0 \quad & \text{otherwise} \end{aligned} \tag{1.20}$$

From the firm's problem, the marginal value of an employed worker to the firm $S_{n,t}$ is given by

$$S_{n,t} = x_t h_t - w_t h_t + \mathbb{E}_t[M_{t+1} S_{n,t+1}(1 - \phi)] \tag{1.21}$$

An additional employed worker supplies the sum of the marginal product of employment net of wages, plus the expected marginal value in next period, in which she remains matched with a probability $1 - \phi$. Similarly, the marginal value of a posted vacancy to the firm $S_{v,t}$ is

$$S_{v,t} = -\kappa_t + \zeta_t q_t + \mathbb{E}_t[M_{t+1} S_{n,t+1} q_t] = 0 \tag{1.22}$$

An additional vacancy incurs posting costs, but provides a chance to hire a worker with a probability q_t in next period. The assumption on free entry yields $S_{v,t} = 0$, which is equivalent to (1.19). In sum, the firm gets the surplus of $S_{n,t} - S_{v,t} = S_{n,t}$, when it recruits an additional worker by filling a vacancy.

1.2.4 Bargaining on Hours Worked and Wages

A bargaining between the matched worker and the firm determines contract terms on hours worked and a wage rate. Let Λ_t denote the joint surplus from an additional match in terms of consumption.

$$\Lambda_t = \frac{J_{n,t} - J_{u,t}}{\lambda_t} + S_{n,t} - S_{v,t} \tag{1.23}$$

Hours worked are efficiently selected to maximize the surplus: the first-order condition for h_t is

$$x_t + \frac{1}{\lambda_t}\frac{\partial U_t^n}{\partial h_t} = 0 \tag{1.24}$$

The wage rate is selected by the alternating-offer wage bargaining proposed by Hall and Milgrom (2008).[10] The matched worker and the firm alternate in making wage proposals. The firm makes the first offer w_t^f. The worker responds to it by exercising one of three options: (a) accept the firm's offer, (b) reject it, prolong the bargain, and make a counter-offer w_{t+1}^h in next period, and (c) abandon the negotiation and exercise

[10]We will discuss the quantitative results of the Nash wage bargaining model under the standard calibration and under the small surplus calibration of Hagedorn and Manovskii (2008) in Section 1.5.1.

the outside option. When the bargaining is delayed in the case of (b), the worker takes unemployment benefits η in current period, while the firm incurs bargaining delay costs ξ. And then the firm becomes a responding party with the same options in next period. When the bargaining is terminated in the case of (c), the worker becomes unemployed and contributes $J_{u,t}/\lambda_t$ to the household, while the firm obtains $S_{v,t}$ that equals zero. The outside options are, however, assumed to be less favorable for both parties than an agreement, which will be accomplished by the calibration.[11] Therefore, taking the outside options is not a credible threat, and matters only when the negotiation breaks down exogenously with a probability δ. Because both parties think through the whole outcomes from a sequence of alternating offers, the firm proposes the just acceptable offer to the worker. Consequently, they do not waste time and resources for the haggling and arrive at an agreement immediately. Therefore, the firm's initial offer becomes the equilibrium wage: $w_t = w_t^f$.

Let $J_{n,t}^f$ and $J_{n,t}^h$ denote the marginal value of an employed worker that the household gets from a wage offer proposed by the firm and by the

[11]To make the bargainers never abandon, the joint value from an agreement should be larger than the joint value from the outside options. Also, it should outweigh the present value from prolonging the negotiation infinitely. Because the joint value from the outside options is bigger than the present value from delaying infinitely, we need to check whether the numerical solutions satisfy the following inequality.

$$\frac{J_{n,t}^f}{\lambda_t} + \left\{ x_t h_t - w_t^f h_t + \left(\frac{\kappa_t}{q_t} - \zeta_t \right) (1 - \phi) \right\} > \frac{J_{u,t}}{\lambda_t} \tag{1.25}$$

worker, respectively. From (1.10), they are given by

$$\frac{J^f_{n,t}}{\lambda_t} = \frac{U^n_t}{\lambda_t} - c_{n,t} + w^f_t h_t + \mathbb{E}_t\left[M_{t+1}\left\{\frac{J^f_{n,t+1}}{\lambda_{t+1}}(1-\phi) + \frac{J_{u,t+1}}{\lambda_{t+1}}\phi\right\}\right] \quad (1.26)$$

$$\frac{J^h_{n,t}}{\lambda_t} = \frac{U^n_t}{\lambda_t} - c_{n,t} + w^h_t h_t + \mathbb{E}_t\left[M_{t+1}\left\{\frac{J^h_{n,t+1}}{\lambda_{t+1}}(1-\phi) + \frac{J_{u,t+1}}{\lambda_{t+1}}\phi\right\}\right] \quad (1.27)$$

Similarly, define $S^f_{n,t}$ and $S^h_{n,t}$ as the marginal value of an employed worker that the firm gains from a wage offer proposed by the firm and by the worker, respectively. From (1.21), they are given by

$$S^f_{n,t} = x_t h_t - w^f_t h_t + \mathbb{E}_t[M_{t+1} S^f_{n,t+1}(1-\phi)] \quad (1.28)$$

$$S^h_{n,t} = x_t h_t - w^h_t h_t + \mathbb{E}_t[M_{t+1} S^h_{n,t+1}(1-\phi)] \quad (1.29)$$

Because the worker is indifferent to the firm's offer, the marginal value of an employed worker to the household from the firm's offer equals the flow value when the worker declines it.

$$\frac{J^f_{n,t}}{\lambda_t} = \delta\frac{J_{u,t}}{\lambda_t} + (1-\delta)\left\{\frac{U^u_t}{\lambda_t} - c_{u,t} + \eta + \mathbb{E}_t\left[M_{t+1}\frac{J^h_{n,t+1}}{\lambda_{t+1}}\right]\right\} \quad (1.30)$$

When the worker turns down w^f_t, the household obtains the marginal value of an unemployed worker with a probability δ, or the sum of the current-period flow value from an unemployed worker plus the expected discounted marginal value of an employed worker from a counter offer w^h_{t+1} with a probability $1-\delta$. In the same manner, the marginal value of an employed worker to the firm from the household's offer equals the flow value when the firm rejects it.

$$S^h_{n,t} = \delta S_{v,t} + (1-\delta)\left(-\xi + \mathbb{E}_t\left[M_{t+1} S^f_{n,t+1}\right]\right) \quad (1.31)$$

When the firm refuses w_t^h, it obtains nothing with probability δ, or invests bargaining delay costs ξ in current period and gets the expected discounted marginal value of an employed worker from a counter offer w_{t+1}^f with probability $1-\delta$. From the indifference conditions (1.30) and (1.31), we can derive the wage offers from the parties.

$$\begin{aligned} w_t^f = \frac{1}{h_t}\Bigg\{ & z_t + (1-\delta)\mathbb{E}_t\left[M_{t+1}\left(\frac{J_{n,t+1}^h}{\lambda_{t+1}} - \frac{J_{u,t+1}}{\lambda_{t+1}}\right)\right] \\ & - (1-\phi-\delta f_t)\mathbb{E}_t\left[M_{t+1}\left(\frac{J_{n,t+1}^f}{\lambda_{t+1}} - \frac{J_{u,t+1}}{\lambda_{t+1}}\right)\right]\Bigg\} \end{aligned} \tag{1.32}$$

$$\begin{aligned} w_t^h = \frac{1}{h_t}\Bigg\{ & x_t h_t + (1-\phi)(1-\delta)\mathbb{E}_t\left[M_{t+1}\left\{-\xi + \left(\frac{\kappa_{t+1}}{q_{t+1}} - \zeta_{t+1}\right)\right\}\right] \\ & - (1-\delta)\left(-\xi + \left(\frac{\kappa_t}{q_t} - \zeta_t\right)\right)\Bigg\} \end{aligned} \tag{1.33}$$

The key difference from the original wage equations of Hall and Milgrom (2008) is that the flow value of unemployment z_t in (1.32) is not constant but procyclical because of the curvature in utility. Therefore, the equilibrium wage moves to offset changes in productivity, which alleviates unemployment volatility. However, z_t becomes less responsive to changes of productivity if ψ increases. In addition, the bargaining termination probability δ and the bargaining delay costs ξ still help making the equilibrium wage partially insulated from productivity. If δ is lower, the role of the outside option $J_{u,t}$ gets smaller in (1.30), and thus the equilibrium wage becomes more inelastic to movements in tightness from the job-finding rate in (1.32). If δ is zero, the resulting wages are completely separated from the labor market.[12] In sum, higher ψ and lower δ induce wages to be more rigid, increasing labor market fluctuations.

1.2.5 Asset prices

Using the stochastic discount factor (1.8), the risk-free rate R_t^f is computed by

$$R_t^f = \frac{1}{\mathbb{E}_t[M_{t+1}]} \tag{1.34}$$

Because the system of equilibrium conditions is homogenous of degree one, a return to holding a equity share equals a return to hiring a worker. From the intertemporal job creation condition (1.19), the stock return R_{t+1}^S is, therefore, given by

$$R_{t+1}^S = \frac{S_{t+1}}{S_t - d_t} = \frac{x_{t+1}h_{t+1} - w_{t+1}h_{t+1} + \left(\frac{\kappa_{t+1}}{q_{t+1}} - \zeta_{t+1}\right)(1-\phi)}{\frac{\kappa_t}{q_t} - \zeta_t} \tag{1.35}$$

And it satisfies the asset Euler equation.[13]

$$1 = \mathbb{E}_t\left[M_{t+1}R_{t+1}^S\right], \quad M_{t+1} = \beta\frac{\lambda_{t+1}}{\lambda_t} \tag{1.36}$$

When positive persistent productivity shocks hit the economy, the stock price capitalizes all future productivity gains on impact. If the wage rate does not absorb too large a fraction of the productivity movements, the stock price increases, discounting higher future cash flows at a lower

[12]On the contrary, if δ goes to one, the equilibrium wage becomes the same as the Nash-bargained wage.

[13]The time subscript of R_t^f and R_{t+1}^S indicates the date on which the relevant payoffs become known. In both cases, the payoffs are realized in period $t+1$.

discount rate. As smaller R^S_{t+1}, or higher M_{t+1}, pushes up the expected payoffs from hiring a new worker in the right-hand side of (1.19), the firm is inclined to invest more resources in recruitment.

If ψ increases, the substitution effect more overwhelms the wealth effect. When R^S_{t+1} declines, the household has a stronger desire to delay temporarily-increased consumption for the future, which encourages the firm to invest more resources in hiring. This tends to push up the stock price further, elevating labor market fluctuations further. Therefore, a higher level of the EIS reinforces the amplification mechanism of labor market fluctuations through the discount rate effect.[14]

1.2.6 Competitive Equilibrium

Let $\Phi_t = (n_t, x_t)$ denote the state vector in period t. The competitive equilibrium for the economy is defined by (a) family's indirect utility J_t, and consumptions of employed and unemployed workers $c_{n,t}$ and $c_{u,t}$, (b) the number of vacancies posted by the firm v_t, and the Lagrange multiplier on the nonnegative vacancy condition ζ_t, (c) hours worked h_t, and the wage rate w_t, (d) the labor market outcomes q_t and f_t, (e) the stochastic discount factor M_{t+1}, (f) the laws of motion for the state Φ_t, such that the following statements hold.

[14]In the MP model, employment is determined by the firm's vacancy posting, to which the substitution and wealth effects from discount rates are more related. On the other hand, hours worked are determined by bargaining, to which the substitution and wealth effects from wages are more relevant.

- J_t maximizes family's problem (1.5) and (1.7). And $c_{n,t}$ and $c_{u,t}$ are the associated consumption rules.

- v_t and ζ_t satisfy the firm's optimality condition (1.19) and the Kuhn-Tucker condition (1.20).

- h_t is chosen by (1.24). And w_t is set by (1.32), (1.33) and $w_t = w_t^f$.

- q_t and f_t are determined by (1.2) and (1.3).

- M_{t+1} is given by (1.8), and $a_t = 1$

- The good market clears.

$$x_t h_t n_t - \kappa_t v_t = n_t c_{n,t} + u_t c_{u,t} \tag{1.37}$$

- The aggregate laws of motion are consistent with the individual decisions, the employment evolution condition (1.4), and the stochastic process of labor productivity (1.14).

1.3 Numerical Solution and Parameterization

To analyze how the desire for consumption smoothing affects labor market fluctuations, we choose three different values of the EIS parameters: $\psi = 0.4$ from Hall and Milgrom (2008), $\psi = 1.0$ that leads to log utility, and $\psi = 2.0$ from Barro (2009) and Gourio (2012). And we conduct the quantitative analysis using calibrations. Section 1.3.1 discusses the numerical solution method, and Section 1.3.2 presents the parameter values.

1.3.1 Computation

The log-linearization is generally used for the quantitative analysis in the search literature. However, the local solution method is not suitable to study the effect of the curvature in utility on unemployment volatility. In addition, Petrosky-Nadeau and Zhang (2013a) show that the log-linearization understates the mean and volatility of unemployment, and overstates the correlation between unemployment and vacancies in the MP model. Therefore, the global solution method is crucial for our quantitative analysis.

Our numerical solution algorithm is based on the policy function iteration with the finite element method. The key goal of the algorithm is to find the equilibrium vacancy-filling rate q_t satisfying the intertemporal job creation condition (1.19) over the state variables, n_t and z_t, which we discretize into an equidistance grid. Petrosky-Nadeau, Zhang, and Kuehn (2013) (with the Nash wage bargaining) and Petrosky-Nadeau and Zhang (2013b) (with the alternating-offer wage bargaining) rely on the projection method proposed by Christiano and Fisher (2000) that is developed to deal with occasionally binding constraints. Their algorithm approximates the conditional expectation in the right-hand side of (1.19) with a polynomial, and solves for q_t. Our algorithm has some advantages over the projection method without paying much computational cost. (a) Our method is more robust to get solutions. The kinds of polynomials used by the projection method are defined on a bounded domain of the state variables. Therefore, endogenous state variables should be updated within the domain interval, the failure of which collapses the algorithm. As a consequence, two studies seem to use the homotopy method to widen a grid of n_t in the model, as well as choosing initial solutions carefully. Also they fail to get solutions for some parameter values of the model. This is not the case with our method based on the finite element method. (b) Our method is easier and simpler to implement for more complex specifications of the model. In particular, allowing both extensive and intensive margins of labor supply in the preference makes it necessary to utilize a non-linear solver not only for the equilibrium vacancy-filling rate q_t but also for hours worked h_t. (c) Our method is more suitable to deal with the non-linearity of the MP model. It is well-known that the projection method cannot fully capture steep curvatures or kinks of solutions. The method of Christiano and Fisher (2000) cannot overcome this disadvantage, because the nonnegative vacancy constraint is not a root for the non-linearity of the model. A supplemental technical appendix contains further details on our solution algorithm.

1.3.2 Calibration

Table 1.1 summarizes the parameter values for the calibrations with three alternative EIS parameters. Because of the nonlinearity, we do not calibrate the model by relying on the steady state equilibrium. Instead, we match moments from simulated data with the corresponding targets from observed data. Throughout the paper we obtain model moments from 10,000 artificial samples, each of which has 956 observations. Because we discard the first 100 observations to eliminate the effect of the initial conditions, the samples span 856 months or 63 years. As the model period is one month, we time-aggregate model-generated data properly in accordance with a frequency of the targets. Table 1.2 contains the performance of three calibrations in matching the targets. The sample period of the observed data is from 1951 to 2013.[15] We describe the data source in more detail in the technical appendix.

Using the HP-filtered[16] real output per hour in the nonfarm business sector, we find that quarterly labor productivity has an autocorrelation of 0.72 and a standard deviation of 0.011. This requires setting $\rho = 0.935$ and $\sigma = 0.006$ at monthly frequency. We approximate the labor productivity process (1.14) with the 41-state Markov chain, using the method of Tauchen (1986).

Among the preference parameters, we set the hours worked curvature to be $\chi = 0.8$, following Hall and Milgrom (2008).[17] Note the empirical

[15]We pick 1951 as the beginning year of the sample period, following the literature. In 1951, the Conference Board began to construct the help-wanted advertising index, which Shimer (2005) uses as a proxy for the stock of vacancies.

[16]Throughout the paper we use a smoothing coefficient of 1,600 to filter quarterly data.

[17]The analysis with the Frisch elasticity of labor supply is based on the traditional assumption that workers determine hours worked taking wages as given. Therefore, it may be not directly applicable to the MP model, where wages are determined by

Table 1.1: Calibration values (monthly)

Parameter	Interpretation	Consumption curvature		
		$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
Technology				
ρ	Persistence of productivity		0.935	
σ	Volatility of productivity		0.006	
Preference				
χ	Hours worked curvature		0.80	
τ	Complementarity in utility	0.5352	-0.2658	-0.2502
φ	Disutility of hours worked	0.7687	1.3061	1.7045
β	Time discount factor		0.9988	
Q	Value of home production	0.354	0.265	0.241
Labor market				
ϕ	Separation rate		0.025	
ι	Elasticity of matching		1.17	
κ	Vacancy-posting costs		0.268	
η	Unemployment benefits		0.041	
Wage bargaining				
ξ	Bargaining delay costs to employer		0.285	
δ	Bargaining termination probability		0.03	

studies using the household data, such as Pistaferri (2003), show that the Frisch elasticity of labor supply is below one for male workers, while it is above one for women, and younger and older men. We calibrate the parameter for disutility of hours worked φ at the point where hours worked h are normalized to be one on average. Chodorow-Reich and Karabarbounis (2014) show that a ratio of consumption between employed and unemployed workers c_u/c_n is 0.79. We determine the complementarity parame-

bargaining and hours worked are set efficiently. This also implies that the utility specification of Chodorow-Reich and Karabarbounis (2014) may not yield the constant elasticity of labor supply with respect to wages in the MP model.

Table 1.2: Matching the calibration targets

Targets	Data	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
Autocorrelation of quarterly labor productivity	0.716	0.719	0.719	0.718
Standard deviation of quarterly labor productivity	0.011	0.011	0.011	0.011
Job-finding rate	0.417	0.402	0.408	0.417
Vacancy/unemployment	0.635	0.576	0.599	0.637
Unemployment rate (%)	5.87	5.86	5.86	5.88
Risk-free rate (A%)	1.38	1.40	1.43	1.45

ter τ to accomplish this target inside the model. We alter the value of home production Q to match the flow value of unemployment of $z = 0.71$ that is required to match the observed average unemployment rate of 5.87% under the standard calibration of the Nash wage bargaining model.[18] We take the time discount factor $\beta = 0.9988$ to match the 3-month T-bill rate of 1.4% per annum.

For the labor market parameters, we use targets from the observed data. As in Hagedorn and Manovskii (2008) and Chodorow-Reich and Karabarbounis (2014), we calculate monthly separation rates as the ratio of the number of unemployed workers for fewer than five weeks in the next month to the number of employed workers in the current month: $\phi_t = u^s_{t+1}/n_t$.[19] This procedure leads us to set ϕ to be the average separation rate of 0.025. To choose the matching function parameter ι and

[18]See Section 1.5.1 for more details

[19]Shimer (2005) points out that this procedure understates the separation rate, because it ignores workers who lose a job but find new one within a month. However, an adjustment of this time-aggregation bias is not consistent with the employment evolution condition, and thus impedes matching targets. Chodorow-Reich and Karabarbounis (2014) show that the bias is negligible, as the separation rates estimated at a monthly frequency and averaged at a quarterly level are similar to those estimated at a quarterly frequency.

the vacancy-posting costs κ, we compute monthly job-finding rates and monthly vacancy/unemployment ratios. For the job-finding rates, we use the employment evolution condition: $f_t = 1-(u_{t+1}-u^s_{t+1})/u_t$. And we find that the average job-finding rate is 0.42. For the vacancy/unemployment ratios, we divide the number of job openings for total nonfarm by the number of unemployed workers. As the Job Openings and Labor Turnover Survey (JOLTS) reports the job openings only after December 2000, we extend the series using two more sources as in Petrosky-Nadeau and Zhang (2013b): the metropolitan life insurance company help-wanted advertising index and the composite help-wanted index of Barnichon (2010). This procedure reveals that the average vacancy/unemployment ratio is 0.64. These estimates imply the vacancy-filling rate of 0.66 ($= f/\theta$) and the unemployment rate of 5.66% ($= \phi/(\phi + f)$) in the steady state. We take the matching function parameter $\iota = 1.17$ to match the average job-finding rate, and vary the vacancy-posting costs κ to match the average vacancy/unemployment ratio inside the model. We set the public benefits $\eta = 0.041$ that is the estimation of Chodorow-Reich and Karabarbounis (2014). In this paper, we neglect the countercyclicality of η, as the portion of η in z is quite small.

For the wage bargaining parameters, we follow Hall and Milgrom (2008). We take the bargaining delay costs $\xi = 0.285$ to match the average unemployment rate of 5.87%. And we set the bargaining termination probability $\delta = 0.03$, which matches the observed unemployment volatility of 0.13 with $\psi = 2.0$.

1.4 Quantitative Results

In this section, we show that three alternative levels of the EIS have very different quantitative results for labor market fluctuations. Section 1.4.1 presents labor market moments from the calibrations of the model. To illustrate intuition underlying the relationship between the EIS and unemployment volatility, Section 1.4.2 and 1.4.3 examine the effect of the desire for consumption smoothing on the flow value of unemployment and the stock returns, respectively. Finally, Section 1.4.4 derives the implications of the results for the magnitude of the EIS.

1.4.1 Labor Market Moments

Table 1.3 reports labor market statistics from simulating the model with labor productivity shocks and their empirical counterparts from the U.S. data. The search literature generally regards the marginal product of employment, rather than labor productivity, as the driving force, because it does not contain the intensive margin of labor supply in the model. To compare with the previous studies, we present labor market moments using the marginal product of employment p_t. And we add impulse responses with respect to labor productivity x_t instead. Note "the flow value of unemployment is procyclical" in this paper means both that z_t rises in respond to increase of p_t and that z_t/h_t rises in respond to increase of x_t. We use the real output per person in the nonfarm business sector as a proxy for the marginal product of employment.

Table 1.3: Labor market moments (quarterly)

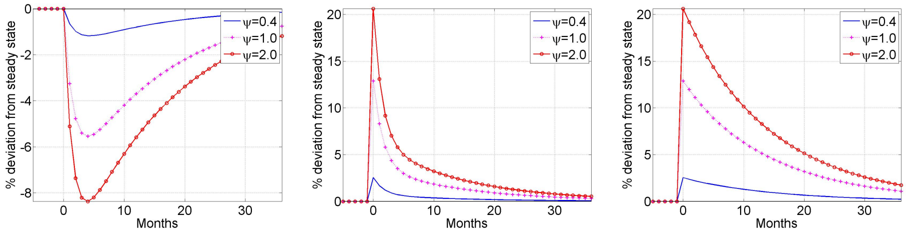
$\hat{x}$ is the percent deviation of x from its trend. We obtain trends of variables using the HP-filter with a smoothing parameter of 1,600. SD(x) and AC(x) denote a standard deviation and an autocorrelation of x, respectively. COR(x_1, x_2) is a correlation between x_1 and x_2.

	Data	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
SD($\hat{u}_t$)	0.129	0.016	0.078	0.129
SD($\hat{v}_t$)	0.143	0.017	0.081	0.137
SD($\hat{\theta}_t$)	0.266	0.029	0.138	0.229
AC($\hat{u}_t$)	0.881	0.802	0.803	0.804
AC($\hat{v}_t$)	0.899	0.416	0.422	0.424
AC($\hat{\theta}_t$)	0.899	0.712	0.712	0.707
COR($\hat{u}_t, \hat{v}_t$)	-0.919	-0.509	-0.507	-0.487
COR($\hat{u}_t, \hat{\theta}_t$)	-0.977	-0.866	-0.863	-0.852
COR($\hat{u}_t, \hat{p}_t$)	-0.232	-0.843	-0.828	-0.817
COR($\hat{v}_t, \hat{\theta}_t$)	0.982	0.871	0.873	0.872
COR($\hat{v}_t, \hat{p}_t$)	0.386	0.889	0.896	0.874
COR($\hat{\theta}_t, \hat{p}_t$)	0.319	0.998	0.994	0.982

As the EIS parameter gets smaller, the volatility of unemployment, vacancies, and labor market tightness becomes larger. In particular, the results under $\psi = 2.0$ are line with the observed labor market fluctuations. Note our global solutions are consistent with Petrosky-Nadeau and Zhang (2013a) in that the negative correlation between unemployment

Figure 1.1: Impulse response of labor market variables to 1% increase in productivity

(a) u_t (b) v_t (c) θ_t



and vacancies, or the slope of the Beverage curve, is much lower than that in the previous studies using the log-linearization. Also, we confirm two drawbacks of the MP model: the correlation between tightness and the marginal product of employment is too high and vacancies are less persistent, compared to the data.

Figure 1.1 shows the impulse response of labor market variables to 1 percent increase in labor productivity. Along the qualitative dimension, the model performs well: in booms, unemployment rate declines and the firm posts more vacancies, boosting labor market tightness. However, the amplification mechanism is very different depending on the magnitude of the desire to smooth consumption. 1 percent increase of productivity leads to 20 percent increase of tightness under $\psi = 2.0$. This elasticity is almost 10 times larger than that resulting from $\psi = 0.4$.

1.4.2 Wage Channel: Procyclical Flow Value of Unemployment

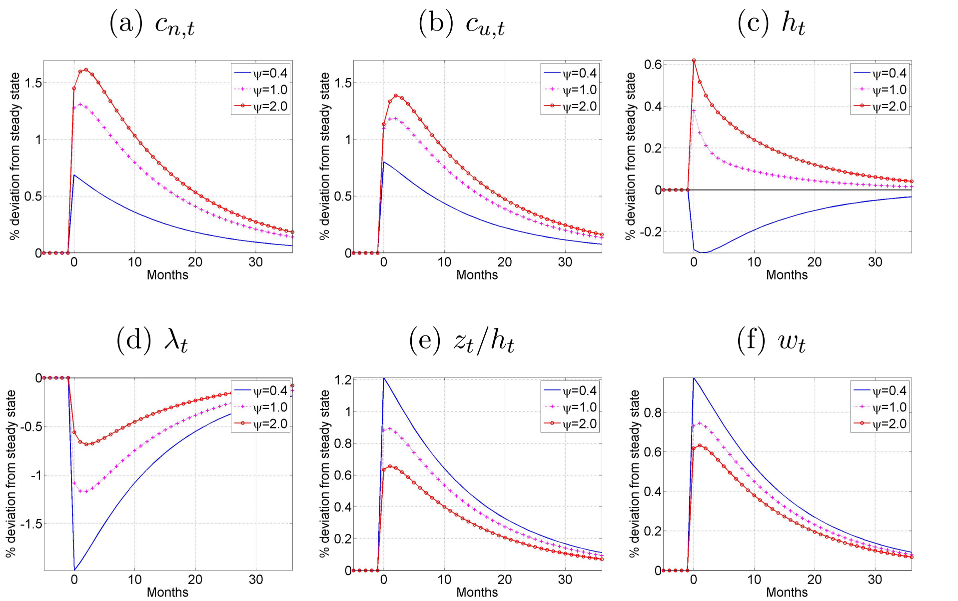
Figure 1.2 illustrates the impulse response of the flow value of unemployment to 1 percent increase in labor productivity. During expansions consumption increases and the marginal utility of consumption declines. This lifts up the flow value of unemployment.

If the EIS becomes higher, larger changes in consumption are tolerable. Also, hours worked increase more in response to positive productivity shocks, as the substitution effect more dominates the wealth effect from the higher wage rate.[20] Therefore, the complementarity between consumption and hours worked more restrains the marginal utility of consumption from diminishing. These are manifested by the lower sensitivity of the marginal utility of consumption to productivity. As a result, the weaker desire for consumption smoothing makes the flow value of unemployment less procyclical and the wage rate more inelastic to changes of productivity.

Table 1.4 reports the cyclicality of the flow value of unemployment from simulations of the model. The flow value of unemployment is procyclical, and as volatile as labor productivity. Consistent with the impulse response, the higher EIS weakens reactions of the marginal utility of consumption, and thus drops the elasticity of the flow value of unemployment per person to the marginal product of employment. This leads to larger unemployment volatility, as the wage rate becomes more insulated from

[20]In contrast, $\psi = 0.4$ counterfactually causes hours worked to be countercyclical, intensifying the sensitivity of the marginal utility of consumption to productivity.

Figure 1.2: Impulse response of the flow value of unemployment to 1% increase in productivity



the driving force.

Following Chodorow-Reich and Karabarbounis (2014), we also compute the data-generated flow value of unemployment by using our utility specification (HM utility). To be specific, (a) we first generate time-series of a ratio of consumption when unemployed to consumption when employed, denoted by $\tilde{\gamma}_t^u$, that makes the first-order conditions for $c_{u,t}$ and $c_{n,t}$ hold exactly in the data, given the parameter values and the data on hours per worker from Cociuba, Prescott, and Ueberfeldt (2012).[21] (b) We obtain consumption series of the employed $\tilde{c}_{n,t}$ by applying the following

[21]Because hours per worker from Cociuba, Prescott, and Ueberfeldt (2012) is available only up to 2011, we reduce the sample period for this analysis to be from 1951 to 2011.

Table 1.4: Cyclicality of the flow value of unemployment in the model (quarterly)
$\hat{x}$ is the percent deviation of x from its trend. We obtain trends of variables using the HP-filter with a smoothing parameter of 1,600. SD(x) and AC(x) denote a standard deviation and an autocorrelation of x, respectively. COR(x_1, x_2) is a correlation between x_1 and x_2. $\mathcal{E}(x_1, x_2)$ is an elasticity of x_1 to x_2, or the regression coefficient of $\hat{x}_1$ on $\hat{x}_2$

	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
SD($\hat{z}_t$)	0.010	0.014	0.014
AC($\hat{z}_t$)	0.71	0.71	0.72
COR($\hat{z}_t, \hat{p}_t$)	1.00	1.00	1.00
$\mathcal{E}(z_t, p_t)$	1.37	1.00	0.84
$\mathcal{E}(\lambda_t, p_t)$	-3.23	-1.11	-0.56
$\mathcal{E}(w_t, p_t)$	1.56	0.68	0.48
$\mathcal{E}(u_t, p_t)$	-1.90	-4.69	-6.27

formula derived from the adding-up identity of the NIPA consumption.

$$\tilde{c}_{n,t} = \frac{c_t^{NIPA}}{\pi_t^n + \pi_t^u \tilde{\gamma}_t^u + \pi_t^o \gamma^o + \pi_t^r \gamma^r} \tag{1.38}$$

where c_t^{NIPA} is consumption expenditures on non-durable goods and services. π_t^n, π_t^u, π_t^o, and π_t^r are the population ratio of the employed (16 years or older), the unemployed (16 years or older), out of the labor force but of working age (16 to 64 years), the retired (over 65 years), respectively. And γ^o and γ^r are the consumption ratio of out of the labor force and the retired over the employed, respectively. We take $\gamma^o = 0.743$ and $\gamma^r = 0.940$ as in Chodorow-Reich and Karabarbounis (2014). (c) Using $\tilde{c}_{n,t}$ and $\tilde{\gamma}_t^u$, we obtain consumption series of the unemployed $\tilde{c}_{u,t}$. (d) Finally, we compute

Table 1.5: Cyclicality of the flow value of unemployment in the data (quarterly)
$\hat{x}$ is the percent deviation of x from its trend. We obtain trends of variables using the HP-filter with a smoothing parameter of 1,600. SD(x) denotes a standard deviation of x. $\mathcal{E}(x_1, x_2)$ is an elasticity of x_1 to x_2, or the regression coefficient of $\hat{x}_1$ on $\hat{x}_2$

	CK utility		HM utility		
	$\psi = 0.727$	$\psi = 1.0$	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
SD($\hat{z}_t$)	0.033	0.043	0.029	0.031	0.032
$\mathcal{E}(z_t, p_t)$	0.90	1.07	0.86	0.78	0.71
	[0.15]	[0.20]	[0.13]	[0.15]	[0.15]
$\mathcal{E}(\lambda_t, p_t)$	-0.44	-0.46	-0.86	-0.33	-0.16
	[0.06]	[0.05]	[0.11]	[0.04]	[0.02]

time-series of the flow value of unemployment.[22] For comparison, we also measure the flow value of unemployment under the utility specification and the parameter values used by Chodorow-Reich and Karabarbounis (2014) (CK utility).[23]

Table 1.5 reports the cyclicality of the flow value of unemployment estimated by the above procedure. First of all, our results using the CK utility are similar to the original estimations of Chodorow-Reich and Karabarbounis (2014), although the data sources and the sample period are different.[24] When ψ of the CK utility increases from 0.727 to 1.0 , the flow value

[22] Chodorow-Reich and Karabarbounis (2014) show that the mean level of $\tilde{c}_{n,t}$ and $\tilde{c}_{u,t}$ are estimated to be 0.543 and 0.430 relative to the mean level of the marginal product of employment. Therefore, we scale down the consumption series so as to be those figures on average, before computing the flow value of unemployment. Also, we adjust the real output per person to be one on average over the sample period. For simplicity, we set $\eta = 0.041$ and $Q = 0.0$.

[23] See Section 1.5.2 for more details on the CK utility.

[24] The elasticity of the flow value of unemployment is slightly lower than that in Chodorow-Reich and Karabarbounis (2014). It is because Chodorow-Reich and

of unemployment becomes more procyclical. The reason is that both the EIS and the complementarity between consumption and hours worked are controlled by only one parameter ψ in the CK utility. Particulary, $\psi = 1$ transforms the CK utility into the log-separable preference. As a consequence, the countercyclicality of the marginal utility of consumption is not anymore lessened by the procyclicality of hours worked from the data. Excluding the non-separability between consumption and hours worked dominates the weaker desire for consumption smoothing in determining the cyclicality of z_t.

The HM utility shows different outcomes, because its ψ does not affect the non-separability between consumption and hours worked. Higher ψ makes the flow value of unemployment less procyclical by inducing the marginal utility of consumption to be more inelastic to changes in the marginal product of employment. This is consistent with the results from simulated data.

1.4.3 Discount Rate Channel: Countercyclical Stock Returns

Figure 1.3 depicts the impulse response of financial market variables to 1 percent *decrease* in labor productivity. When negative productivity shocks arrive, the stock price plunges, which discounts lower future cash flows at a higher discount rate. As a result, investment in hiring declines. In contrast,

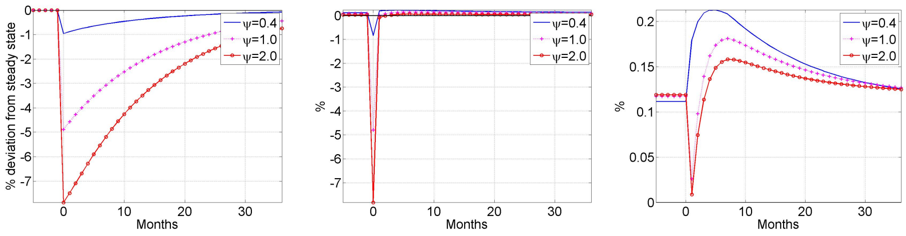
Karabarbounis (2014) correct measurement error for $\hat{p}_t$ by instrumenting with the cyclical component of the unadjusted TFP series of Fernald (2014).

the risk-free rate is not affected in the initial period. The significant drop in the value of stocks relative to bills upon impact coincides with increase in the marginal utility of consumption. In the subsequent period, the risk-free rate falls when $\psi \geq 1.0$, because consumption keeps declining by the strong substitution effect.[25] This corresponds to "flight to quality": the household tries to shift the portfolio towards safer assets.

When the EIS becomes higher, the households would like to save more, reinforcing the countercyclicality of stock returns. This suggests that the amplification mechanism from the discount rate effect also critically depends on the degree of the willingness to smooth consumption: the higher ψ corresponds to larger unemployment volatility, as well as greater movements in output and consumption.

Figure 1.3: Impulse response of financial market variables to 1% decrease in productivity

(a) S_t (b) R_t^S (c) R_{t-1}^f



The financial market moments from simulations of the model in Table 1.6 also confirm the relationship between the EIS and the stock returns. The higher ψ shows the larger volatility of the excess stock returns. Par-

[25] See the persistence of consumptions when $\psi \geq 1$ in Figure 1.2a and 1.2b

Table 1.6: Financial market moments (quarterly)

E(x) and SD(x) denote a mean and a standard deviation of x, respectively. $A\%$ denotes the annualized real percent return.

	Data	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
$SD(R_t^f)$ (A%)	2.60	2.32	1.32	0.82
$SD(R_{t+1}^S - R_t^f)$ (A%)	18.37	2.00	10.52	16.79
$E(R_{t+1}^S - R_t^f)$ (A%)	7.39	0.06	0.23	0.22

Table 1.7: Labor market moments when $z_t = \bar{z}p_t$ (quarterly)

$\hat{x}$ is the percent deviation of x from its trend. We obtain trends of variables using the HP-filter with a smoothing parameter of 1,600. SD(x) denotes a standard deviation of x. $\mathcal{E}(x_1, x_2)$ is an elasticity of x_1 to x_2, or the regression coefficient of $\hat{x}_1$ on $\hat{x}_2$. $A\%$ denotes the annualized real percent return.

	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
$\mathcal{E}(z_t, p_t)$	1.00	1.00	1.00
$\mathcal{E}(w_t, p_t)$	1.60	0.69	0.54
$SD(R_t^f)$ (A%)	2.25	1.34	0.77
$SD(R_{t+1}^S - R_t^f)$ (A%)	6.04	10.60	12.55
SD($\hat{u}_t$)	0.050	0.088	0.105
SD($\hat{v}_t$)	0.050	0.090	0.108
SD($\hat{\theta}_t$)	0.087	0.154	0.184

ticularly, the standard deviation of the excess stock returns under $\psi = 2.0$ is close to the data. On the other hand, the higher EIS leads to the lower standard deviation of the risk-free rates. Many financial studies have difficulty in achieving both the low risk-free rate volatility and the high stock return volatility simultaneously.[26]

[26] Jermann (1998), Boldrin, Christiano, and Fisher (2001), Kaltenbrunner and Lochstoer (2010), etc

Table 1.8: Labor market moments when the firm discounts with β (quarterly)
$\hat{x}$ is the percent deviation of x from its trend. We obtain trends of variables using the HP-filter with a smoothing parameter of 1,600. SD(x) denotes a standard deviation of x. $\mathcal{E}(x_1, x_2)$ is an elasticity of x_1 to x_2, or the regression coefficient of $\hat{x}_1$ on $\hat{x}_2$

	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
$\mathcal{E}(z_t, p_t)$	1.18	0.96	0.82
$\mathcal{E}(w_t, p_t)$	1.36	0.72	0.51
$\mathcal{E}(u_t, p_t)$	4.62	-1.72	-4.58
SD($\hat{u}_t$)	0.046	0.029	0.092
SD($\hat{v}_t$)	0.048	0.030	0.097
SD($\hat{\theta}_t$)	0.081	0.051	0.164

To verify the discount rate channel in isolation, we eliminate difference in the wage channel by setting $z_t = \bar{z}p_t$ for all ψ, and then recalculate the labor market moments from the model in Table 1.7. Although the elasticity of the flow value of unemployment to the marginal product of employment equals one across all values of ψ, the higher EIS still involves the more rigid wages due to the bargaining delay costs and the bargaining termination probability together with the more procyclical hours worked. In addition, stock returns fluctuate further with the higher EIS. Consequently, the higher ψ leads to the larger labor market fluctuations.

To measure the effect of the discount rate channel, we exclude the countercyclical stock returns by assuming that the firm discounts future profits with the constant discount factor in the model: we replace M_{t+1} with β in the equilibrium equations related to the firm, (1.16), (1.19), and

(1.33). Table 1.8 reports the results implied by the alternative assumption. $\psi = 1.0$ and $\psi = 2.0$ present smaller labor market fluctuations than those in the baseline model. This suggests that the lack of the discount rate channel reduces unemployment volatility. In the case of $\psi = 0.4$, labor market fluctuations become larger. However, unemployment becomes counterintuitively procyclical, as the absence of the countercyclical stock returns lowers the expected discounted future payoffs of the firm.

1.4.4 Implications for the Elasticity of Intertemporal Substitution

There is a considerable debate in the macroeconomics and finance literature about the magnitude of the EIS. Hall (1988) and Campbell (1999) estimate the EIS to be close to zero using the aggregate data. Attanasio and Weber (1993) also estimate the EIS to be below one using the household-level data, although their estimate is higher than those from the aggregate data. On the contrary, Attanasio and Vissing-Jorgensen (2003), Gruber (2006), and van Binsbergen, Fernández-Villaverde, Koijen, and Rubio-Ramírez (2012) estimate the EIS to be in excess of one. In addition, many challenge the low EIS, because it incurs counterfactual implications in some models. In the long-run risk model of Bansal and Yaron (2004), the EIS below one causes that higher expected growth and lower uncertainty decrease asset prices. In the disaster-risk model of Gourio (2012) and Nakamura, Steinsson, Barro, and Ursúa (2013), the low

EIS induces the risk premium to be procyclical. In our results of the MP model, the following observations provide evidence against a low level of the EIS.

First, we regress the quarter $t + 1$ consumption growth rate on the quarter t risk-free rate in model-generated data as in Hall (1988). We obtain the EIS estimate of 0.18 with the EIS parameter of $\psi = 2.0$. This estimate is substantially lower than one.[27] Bansal and Yaron (2004) also obtain the EIS estimate of 0.62 in the long-run risk model with the parameter value of 1.5, while Gourio (2012) gets 0.36 in the disaster risk model with the parameter value of 2.0. These results support the argument that the regression of Hall (1988) may be misspecified and create the downward bias.[28]

Second, a low level of the EIS is inconsistent with the observed behavior of hours worked. It is well-known that hours worked are highly correlated with output and employment.[29] However, Figure 1.2c illustrates that $\psi = 0.4$ brings about countercyclical hours worked in contrast to $\psi = 2.0$. We also gain the same outcomes in the models with the Nash wage bargaining (Figure 1.5b) and with the utility specification of Chodorow-Reich and Karabarbounis (2014) (Figure 1.6a). The low EIS indicates that the

[27] The EIS parameters of $\psi = 0.4$ and $\psi = 1.0$ generate the EIS estimate of 0.06 and 0.15, respectively.

[28] Guvenen (2006) shows that the downward bias can be corrected by including the conditional variance of consumption growth in the estimation.

[29] See Ohanian and Raffo (2012) and Nakajima (2012) for more details

wealth effect overwhelms the substitution effect from the higher wage rate during booms. Thus, it causes labor hours to fall in response to positive productivity shocks. This is not the case with the high EIS.

Third, the low EIS implies the negative autocorrelation of dividends. In Figure 1.4, dividends in the calibration of $\psi = 0.4$ initially increase in response to positive productivity shocks.[30] However, they decline thereafter, which contradicts the observed persistence of dividends. In the case of Chodorow-Reich and Karabarbounis (2014), whose utility function allows only a low level of the EIS for obtaining the complementarity between consumption and hours simultaneously, dividends initially drop to positive productivity shocks. Consequently, the stock prices counterintuitively are countercyclical. These results are mainly driven by excessively procyclical wages that cause the firm to experience deficits during booms. In sum, the large wealth effect from the low EIS discourages the firm to invest in hiring during expansions, removing the persistence of the firm's profits.

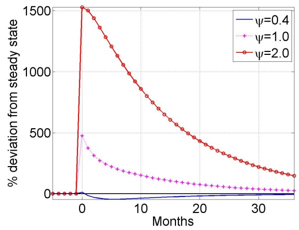
1.5 Extensions and Robustness

This section discusses different approaches to modeling, and conducts the sensitivity analysis. Section 1.5.1 shows the results from the Nash wage bargaining model under the standard calibration and under the small sur-

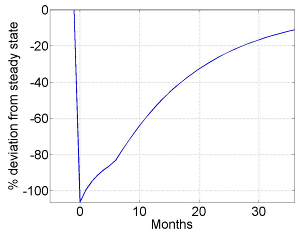
[30]The excess response of dividends to productivity is induced by too high price/dividend ratios generated by the linear production and the dividend payout policy in the model. The decreasing-return-to-scale production or adding physical capital into production may enable the model to generate the realistic level of the price/dividend ratios, which is beyond the scope of the paper.

Figure 1.4: Impulse response of dividends to 1% increase in productivity for different utilities

(a) Hall and Milgrom (2008)



(b) Chodorow-Reich and Karabarbounis (2014)



plus calibration of Hagedorn and Manovskii (2008). Section 1.5.2 and 1.5.3 present the results with the utility specification used by Chodorow-Reich and Karabarbounis (2014) and with the recursive preference of Epstein and Zin (1989), respectively. Section 1.5.4 discusses the effect of altering wage bargaining parameters: raising the bargaining termination probability, lowering the bargaining delay costs, and making the bargaining delay costs procyclical. Finally, Section 1.5.5 reports the impact of adding the fixed component into the vacancy-posting costs.

1.5.1 Nash Wage Bargaining

The standard MP model postulates that the matched worker and the firm split the joint surplus by setting a wage rate through the Nash bargaining. Let $\omega \in (0, 1)$ to be a relative bargaining power of the worker. Then the worker and the firm receive $\omega\Lambda_t$ and $(1-\omega)\Lambda_t$ from the match, respectively. And the equilibrium wage is set by

$$w_t = \frac{1}{h_t}\Big\{\omega\left[x_t h_t + \theta_t \kappa_t\right] + (1-\omega) z_t\Big\} \tag{1.39}$$

Table 1.9: Calibration values for the Nash wage bargaining (monthly)

Parameter	Standard			Hagedorn-Manovskii		
	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
Preference						
φ	0.7914	1.3115	1.7070	0.7902	1.3110	1.7067
Q	0.360	0.267	0.242	0.916	0.621	0.547
Labor market						
κ		0.453			0.445	
Wage bargaining						
ω		0.5			0.052	

The search literature typically sets ω by appealing to the Hosios (1990) condition that opening a vacancy is socially efficient when the bargaining power of the worker equals the unemployment elasticity parameter of the Cobb-Douglas matching function. For example, Shimer (2005) and Pissarides (2009) use $\omega = 0.4$ and $\omega = 0.5$, respectively. As a proxy for z_t, it is common to use the average ratio of benefits to wages. The replacement rates are generally estimated to be 0.2 in the U.S. and 0.7 in Europe. Given these parameter values, the Nash-bargained wages are too closely linked to productivity even with constant z_t. This is the unemployment volatility puzzle suggested by Shimer (2005).

To resolve the puzzle, Hagedorn and Manovskii (2008) proposes the calibration strategy of reducing the worker's bargaining power and pining up the flow value of unemployment close to the marginal product of employment. They set ω and z_t to match the labor market tightness and the elasticity of wages to the marginal product of employment in the data.

Table 1.10: Labor and financial market moments in the Nash wage bargaining (quarterly)

$\hat{x}$ is the percent deviation of x from its trend. We obtain trends of variables using the HP-filter with a smoothing parameter of 1,600. $\mathrm{E}(x)$ and $\mathrm{SD}(x)$ denote a mean and a standard deviation of x, respectively. $\mathcal{E}(x_1, x_2)$ is an elasticity of x_1 to x_2, or the regression coefficient of $\hat{x}_1$ on $\hat{x}_2$. $A\%$ denotes the annualized real percent return.

	Standard			Hagedorn-Manovskii		
	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$	$\psi = 0.4$	$\psi = 1.0$	$\psi = 2.0$
$\mathrm{SD}(\hat{u}_t)$	0.005	0.011	0.016	0.041	0.022	0.076
$\mathrm{SD}(\hat{v}_t)$	0.005	0.011	0.016	0.042	0.022	0.078
$\mathrm{SD}(\hat{\theta}_t)$	0.008	0.020	0.027	0.072	0.039	0.133
$\mathcal{E}(\lambda_t, p_t)$	-3.04	-0.93	-0.44	-2.39	-0.96	-0.49
$\mathcal{E}(z_t, p_t)$	1.34	0.95	0.80	1.53	0.96	0.73
$\mathrm{E}(z_t)$	0.705	0.706	0.706	0.969	0.968	0.968
$SD(R_t^f)$ (A%)	2.359	1.361	0.744	2.666	1.327	0.712
$SD(R_{t+1}^S - R_t^f)$ (A%)	0.283	1.223	1.827	6.256	2.872	9.881
$\mathcal{E}(w_t, p_t)$	1.61	0.79	0.64	1.63	0.75	0.49
$\mathcal{E}(u_t, p_t)$	-0.52	-0.65	-0.76	4.33	-1.30	-3.73

In (1.39), lower ω makes w_t more inelastic to movements in labor market tightness. And higher z_t increases w_t, causing smaller surplus from the match. If z_t is constant, firm's profits, therefore, respond significantly in percentage terms to changes in the marginal product of employment. As a result, the firm becomes more inclined to change the number of vacancies drastically.

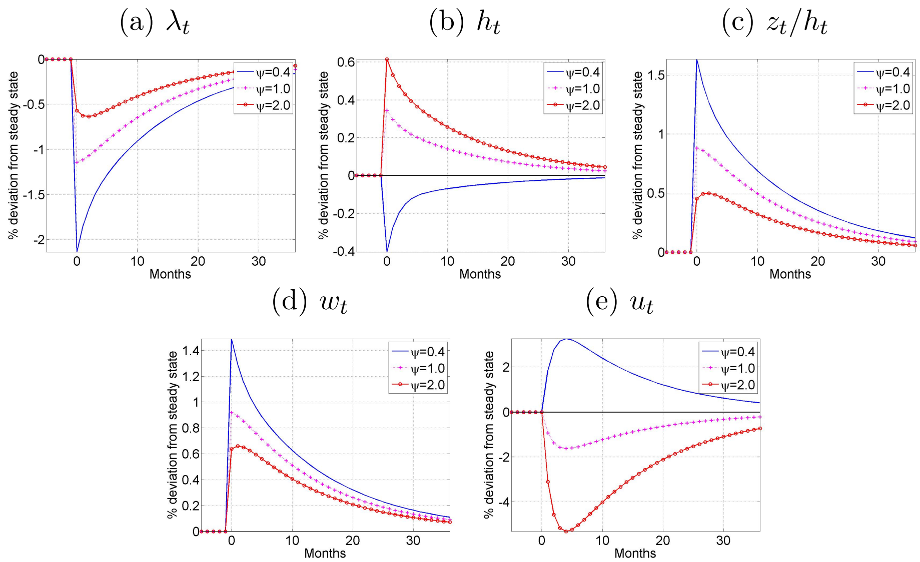
However, adding the curvature of utility to the MP model causes the flow value of unemployment to co-move with productivity. In the alternating-offer wage bargaining, the worker's threat is the disagreement payoffs that depend not only on z_t but also on ξ and δ. In the Nash wage bargaining, it is the outside option payoffs that rely only on z_t. Because the flow value of unemployment reacts flexibly to productivity, the Nash-bargained wages are more vulnerable to labor market conditions than the alternating-offer-bargained wages. As a consequence, the Nash-bargained wages reduce variations in firm's margin even under the small surplus calibration. Also, the more flexible wages hamper the amplification mechanism from the countercyclical stock returns. These depress the firm's incentive to open new vacancies.

To see how the curvature of utility affects unemployment volatility in the MP model with the Nash-bargained wages, we carry out the same quantitative analysis as before for the standard calibration and for the small surplus calibration of Hagedorn and Manovskii (2008). The parameter values are listed in Table 1.9. For the standard calibration, we set the bargaining weight of workers to be $\omega = 0.5$, following Pissarides (2009). And we vary the value of home production Q to set the average flow value of unemployment $z_t = 0.71$. This value is necessary to match the observed unemployment rate of 5.87%. Finally, we pick the vacancy-posting costs $\kappa = 0.453$ to match the observed tightness of 0.64. For the small surplus calibration, we take $\omega = 0.052$, following Hagedorn and Manovskii (2008). We alter Q for $z_t = 0.968$ that generates the observed unemployment rate. And, we set $\kappa = 0.47$ to match the observed vacancy/unemployment ratio. Note the original calibration strategy of Hagedorn and Manovskii (2008) is infeasible because z_t is time-varying. Other parameters have the same value as in the calibration of the alternating-offer wage bargaining model in Table 1.1.

Table 1.10 reports the statistics of interest computed from the Nash wage bargaining model. Under the standard calibration, the elasticity of w_t to p_t is higher than that in the alternating-offer wage bargaining, although the elasticity of z_t to p_t is slightly lower. Also, the excess stock returns display much lower fluctuations. Therefore, unemployment volatility is quite small. However, the higher EIS reduces the procyclicality of the flow value of unemployment and increases the countercyclicality of the discount rates, raising labor market fluctuations. This confirms the relationship between the EIS and unemployment volatility from the wage channel and the discount rate channel.

The calibration strategy of Hagedorn and Manovskii (2008) presents similar results to the standard calibration. However, the small surplus generates several interesting differences. First, the elasticity of z_t to p_t becomes more sensitive to the level of the EIS than in the standard calibration. Therefore, w_t from $\psi = 2.0$ reacts less to p_t, which leads to larger unemployment volatility than in the standard calibration. Second, $\psi = 0.4$ shows larger labor market fluctuations than $\psi = 1.0$. However, this result comes from the counterfactual mechanism: unemployment climbs up during booms because wages respond excessively to productivity despite smaller margin of the firm. Figure 1.5 illustrates the impulse response of labor market variables to 1% increase in productivity under the calibration of Hagedorn and Manovskii (2008). In the case of $\psi = 0.4$, the strong desire for consumption smoothing causes the elasticity of w_t to x_t to be well over one. Moreover, hours worked decline in response to positive productivity shocks. Therefore, the firm undergoes losses during booms, dropping vacancies.

Figure 1.5: Impulse response to 1% increase in productivity in Hagedorn and Manovskii (2008)



(a) λ_t (b) h_t (c) z_t/h_t (d) w_t (e) u_t

1.5.2 Utility of Chodorow-Reich and Karabarbounis (2014)

To measure the flow value of unemployment from the observed data, Chodorow-Reich and Karabarbounis (2014) adopt the following utility specification, which is also used by Shimer (2010) and Trabandt and Uhlig (2011).

$$U_t(c_t, h_t) = \frac{1}{1-1/\psi}\left[c_t^{1-1/\psi}\left(1 - \frac{(1-1/\psi)\varphi}{1+1/\chi}h_t^{1+1/\chi}\right)^{1/\psi} - 1\right] + Q \quad (1.40)$$

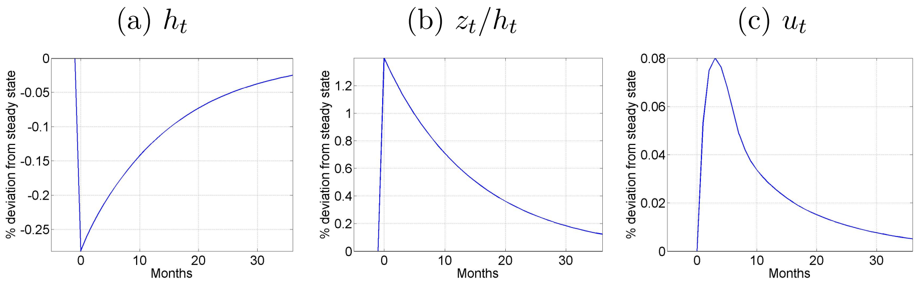
ψ determines both the EIS and the non-separability between consumption and hours worked. And the Frisch elasticity of labor supply is constant at χ. Other parameters play the same role as in the baseline utility specification of (1.6): φ decides the disutility of hours worked, and Q parameterizes the additional utility from home production. Note $\psi < 1$ is required to make the marginal utility of consumption higher when workers are employed. In addition, higher ψ reduces both the desire for consumption smoothing and the complementarity between consumption and hours worked at the same time. The less costs of adjusting consumption caused by higher ψ alleviate the procyclicality of z_t. On the other hand, more separability between consumption and hours worked reduces the willingness to counteract decrease of the marginal utility caused by larger consumption in booms by raising hours worked. This elevates the procyclicality of z_t. Therefore, this utility function is inappropriate to analyze the effect of adjusting the EIS on unemployment volatility.

With the quantitative analysis, we derive the labor market volatility implied by the CK utility. Following Chodorow-Reich and Karabarbounis (2014), we take $\psi = 0.7267$ and $\chi = 0.7$. Chodorow-Reich and Karabarbounis (2014) use an additional consumption parameter c_0 to make this value of ψ compatible with the estimated level of consumptions, $c_n = 0.543$

and $c_u = 0.430$. Therefore, we also include $c_0 = 0.4$ in the resource constraint (1.37) to generate the level of consumptions on average inside the model. c_0 can be interpreted as consumption expenditures by out of the labor force and the government. Other parameters are chosen under the same calibration strategy as before.[31]

Consistent with the results with the HM utility of the low EIS, the CK utility counterfactually features the negative response of hours worked to positive productivity shocks in Figure 1.6a. In addition, the CK utility induces the flow value of employment to be highly procyclical in Figure 1.6b and the first column of Table 1.11. This intensifies the sensitivity of the wage rate to the marginal product of employment and subdues the discount rate effect. As a result, the CK utility involves extremely low labor market fluctuations.

Figure 1.6: Impulse response to 1% increase in productivity in Chodorow-Reich and Karabarbounis (2014)



[31] $Q = 0.818$ and $\varphi = 1.7169$ are selected inside the model.

Table 1.11: Sensitivity Analysis (quarterly)

$\hat{x}$ is the percent deviation of x from its trend. We obtain trends of variables using the HP-filter with a smoothing parameter of 1,600. E(x) and SD(x) denote a mean and a standard deviation of x, respectively. $\mathcal{E}(x_1, x_2)$ is an elasticity of x_1 to x_2, or the regression coefficient of $\hat{x}_1$ on $\hat{x}_2$. $A\%$ denotes the annualized real percent return.

	CK utility	Recursive preference	Higher δ	Lower ξ	Procyclical ξ	Fixed vacancy posting costs
$\mathcal{E}(\lambda_t, p_t)$	-2.69	-0.56	-0.49	-0.55	-0.48	-0.61
$\mathcal{E}(z_t, p_t)$	1.55	0.84	0.80	0.82	0.81	0.85
E(z_t)	0.704	0.706	0.744	0.744	0.706	0.706
$SD(R_t^f)$ (A%)	2.26	0.83	0.73	0.81	0.72	0.95
$SD(R_{t+1}^S - R_t^f)$ (A%)	0.38	16.82	9.32	16.27	7.82	15.16
$E(R_{t+1}^S - R_t^f)$ (A%)	-0.01	0.25	0.11	0.22	0.09	0.18
$\mathcal{E}(w_t, p_t)$	1.48	0.48	0.57	0.49	0.58	0.50
$\mathcal{E}(u_t, p_t)$	0.06	-6.29	-3.54	-6.07	-2.97	-8.11
SD($\hat{u}_t$)	0.001	0.129	0.071	0.124	0.060	0.166
SD($\hat{v}_t$)	0.001	0.137	0.073	0.132	0.062	0.183
SD($\hat{\theta}_t$)	0.001	0.230	0.126	0.221	0.107	0.302

1.5.3 Recursive Preference

From (1.34) and (1.36), we can derive the following equation for the expected excess stock returns.

$$\mathbb{E}_t\left[R_{t+1}^S\right] - R_t^f = -\frac{COV\left[\lambda_{t+1}, R_{t+1}^S\right]}{\mathbb{E}_t\left[\lambda_{t+1}\right]} \tag{1.41}$$

From the main results, we have seen that the excess stock returns show significant volatility. In addition, stocks pay off poorly during recessions, when consumption is low. Thus, (1.41) indicates that stocks must yield a considerable return-premium over bills in normal times to get the household to hold them. However, the household is able to absorb productivity shocks to the stock price not only with changes in consumptions of the employed and the unemployed, but also with changes in hours.[32] Therefore, the average excess stock returns are much lower than in the data as in Table 1.6. To see whether higher risk aversion raises the expected excess stock returns, we extend the baseline model by adding the recursive preference of Epstein and Zin (1989): we replace (1.5) with the following household problem.

$$J_t = \max_{c_{n,t}, c_{u,t}} n_t U_t(c_{n,t}, h_t) + u_t U_t(c_{u,t}, 0) + \beta \left(\mathbb{E}_t \left[J_{t+1}^{1-\gamma} \right] \right)^{\frac{1}{1-\gamma}} \tag{1.42}$$

where γ determines the risk aversion separately from ψ. The stochastic discount factor is then given by

$$M_{t+1} = \frac{\partial J_t / \partial c_{u,t+1}}{\partial J_t / \partial c_{u,t}} = \beta \left(\frac{\lambda_{t+1}}{\lambda_t} \right) \left(\frac{J_{t+1}}{\mathbb{E}_t [J_{t+1}^{1-\gamma}]^{\frac{1}{1-\gamma}}} \right)^{-\gamma} \tag{1.43}$$

In the second column of Table 1.11, the recursive preference of $\gamma = 10.0$ and $\psi = 2.0$ generates essentially the same outcomes as in the baseline model. This result shows that the ability of the household to absorb shocks along consumption and labor margins depresses the risk premium in spite of the high volatility of stock returns. Thus, we cannot appeal to the perfect insurance assumption to generate the observed level of the equity premium in the MP model equipped with the intensive margin of labor supply.

[32] Swanson (2012) shows that risk aversion varies depending on the household's labor margin.

1.5.4 Wage Bargaining Parameters

The bargaining termination probability δ and the bargaining delay costs ξ are the critical parameters to induce the equilibrium wage to be partially isolated from productivity even with the procyclical flow value of unemployment. To evaluate their importance in the model, we compute model moments under $\psi = 2.0$ for alternative parameter values of δ and ξ. First, we increase δ to 0.1, rather than 0.03 in the baseline calibration. This requires Q to increase from 0.241 to 0.286 for matching the observed unemployment rate. In the third row of Table 1.11, the volatility of labor market variables becomes substantially smaller, although the response of the flow value of unemployment to the marginal product of employment varies little. δ affects the wage rigidity meaningfully, because it directly controls the relative contribution of the flow value of unemployment to the alternating-offer-bargained wages. Second, we reduce ξ from 0.2850 to 0.2444, which is necessary to have the same value of $Q = 0.286$ as in the case of lowering δ. Lowering ξ does not alter labor market fluctuations markedly in the fourth row of Table 1.11. The quantitative results are robust to change in ξ, because ξ is only a part of components that affect the continuation values in the equilibrium wage.

The alternating-offer-bargained wages are relatively insensitive to productivity because ξ is assumed to be constant independent of productivity. To evaluate the importance of this assumption, we replace ξ with $\xi_t = \xi p_t$, which implies the elasticity of the bargaining delay costs to the marginal product of employment equals one. In the fifth column of Table 1.11, the procyclical bargaining delay costs increase the sensitivity of the wage rate to the marginal product of employment, and thus diminish labor market fluctuations. However, unemployment volatility is still much higher than that in the MP model with the Nash-bargained wages, although the setting of ξ_t seems to result in too high procyclicality of the bargaining delay costs. We leave it for future research to assess the level of the bargaining termination probability and the cyclicality of the bargaining delay costs empirically.

1.5.5 Fixed Component in Vacancy-Posting Costs

Under the constant vacancy-posting costs $\kappa_t = \kappa$, the marginal cost of hiring is κ/q_t in the left-hand side of (1.19). Because the vacancy-filling rate is decreasing in labor market tightness ($q'(\theta_t) < 0$), the marginal cost of hiring is highly procyclical, which hinders the firm from holding more vacancies during booms. This is the outcome of the externalities that the household and the firm do not internalize the adverse effects of their search decisions in the labor market. To reduce the procyclicality of the marginal cost of hiring, Mortensen and Nagypál (2007) and Pissarides (2009) suggest the fixed component in the vacancy-posting costs as follows.

$$\kappa_t = \kappa_v + \kappa_f q_t \tag{1.44}$$

Under the above specification, the marginal cost of hiring involves a proportional component κ_v/q_t and a fixed component κ_f. Because κ_f makes yields on posting a vacancy less countercyclical, it tends to improve the performance of the MP model. To confirm this intuition, we replace $\kappa = 0.268$ with $\kappa_v = 0.17$ and $\kappa_f = 0.14$ in the baseline calibration with $\psi = 2.0$, and carry out the same quantitative analysis. Note this does not change the model's performance in matching the calibration targets. In the final column of Table 1.11, the fixed component boosts labor market fluctuations substantially, although it induces excess stock returns to be less volatile. Note Hall (2014) also reaches similar conclusion that the fixed component of the vacancy-posting costs helps lowering the implied volatility of the discount rates to account for the realistic increase in unemployment during recessions.

1.6 Conclusion

This paper embeds the curvature of utility into the MP model with both extensive and intensive margins of labor supply, and shows that the EIS plays an important role to make the MP model account for the observed unemployment volatility. The high EIS diminishes the procyclicality of the flow value of unemployment, and thus undermines wages from absorbing productivity shocks. It also widens variations in the expected discounted payoffs from hiring a new worker by reinforcing the countercyclicality of stock returns. Therefore, a high level of the EIS are necessary to replicate labor market fluctuations in the data.

The MP model, including our model, has the well-known shortcoming that the correlation of labor market tightness and productivity is too high compared to the data, which is often overlooked in the literature. As a result, the equilibrium wage is required to be insulated both from productivity and labor market tightness to resolve the unemployment volatility puzzle, as Hall (2014) points out. However, the employment evolution condition (1.4) indicates that unemployment fluctuates only by movements in labor market tightness.[33] If we model the sluggish response of labor market tightness to productivity (Fujita and Ramey, 2007), the equilibrium wage is necessary to be inelastic only to labor market tightness. Then, the Nash-bargained wages under the small surplus calibration and the alternating-offer-bargained wages with the procyclical bargaining delay costs may produce larger unemployment volatility than in our results in the face of the procyclical flow value of unemployment. The link between unemployment volatility and internal propagation in the MP model could be an important research direction.

[33] The following equation is equivalent to the employment evolution condition (1.4) and $n_t = 1 - u_t$.

$$u_{t+1} = \phi(1 - u_t) + (1 - f(\theta_t))u_t \tag{1.45}$$

Technical Appendix

Data

The following data are for the matching targets and the main analyses. The sample period is January 1951 to December 2013. We report the FRED codes in parentheses for data that we download from the Federal Reserve Economic Data of FRB St. Louis.

- Monthly
  - Employment: employed (CE16OV), thousands of persons, SA, CPS, BLS
  - Unemployment: unemployed (UNEMPLOY), thousands of persons, SA, CPS, BLS
  - Short-term unemployment: number of civilians unemployed - less than 5 weeks (UEMPLT5), thousands of persons, SA, CPS, BLS
  - Vacancies: total nonfarm job openings (JTSJOL), level in thousands, SA, JOLTS, BLS
    - Following Petrosky-Nadeau and Zhang (2013b), we extend the series before December 2000 using growth rates of two more sources for job openings
    - April 1929 to December 1959: Metropolitan Life Insurance company help-wanted advertising index

    - (M0882AUSM349NNBR), 1947-1949=100, NSA, NBER, seasonally adjusted by X-12-ARIMA
    * January 1960 to November 2000: composite help-wanted index of Barnichon (2010), 1987=100, SA, https://sites.google.com/site/regisbarnichon/
  - Value-weighted market returns all NYSE, Amex,and Nasdaq stocks including dividends, CRSP
  - Three-month Treasury bill rates, CRSP
  - Rates of change in consumer price index, CRSP
  - Unemployment rate: Civilian Unemployment Rate (UNRATE), percent, SA, CPS, BLS

- Quarterly

  - Labor productivity: nonfarm business sector real output per hour of all persons (OPHNFB), 2009=100, SA, BLS

The following data are used to estimate the quarterly flow value of unemployment, following Chodorow-Reich and Karabarbounis (2014). The sample period is January 1959 to December 2011, which is selected based on the data availability of hours worked.

- Monthly

- Population: Civilian Noninstitutional Population 16 years and over, thousands of persons, NSA, CPS, BLS
- Population older than 65 years: Civilian Noninstitutional Population 65 years and over, thousands of persons, NSA, CPS, BLS

• Quarterly

- Unemployment: unemployed, thousands of persons, SA, CPS, BLS
- Employment: employed, thousands of persons, SA, CPS, BLS
- Labor Force: Civilian Labor Force 16 years and over, thousands of persons, NSA, CPS, BLS
- Labor Force older than 65 years: Civilian Labor Force 65 years and over, thousands of persons, NSA, CPS, BLS
- Marginal product of employment: real output per person in the nonfarm business sector (PRS85006163), SA, NIPA, BLS
- Consumption: real personal consumption expenditures for nondurable goods (PCNDGC96) and services (PCESVC96), billions of chained 2009 dollars, SA, NIPA, BEA
  - We extend the historic series using the quantity indexes: nondurable goods (DNDGRA3Q086SBEA), services (DSERRA3Q086SBEA)

– Hours per worker: CPS hours worked per noninstitutional population 16 to 64 years of Cociuba, Prescott, and Ueberfeldt (2012)

Solving for Equilibrium

Initialization

We set up equidistance grid points over the employment n_t:
$G^n = \{n^1, \cdots, n^{T_n}\}$, where the number of grid points $T_n = 61$, lower bound $n^1 = 0.70$, and upper bound $n^{T_n} = 0.99$. A range of the grid is large enough so that the boundaries are never hit in simulations. We use the piecewise-linear interpolation outside the grid points. Following Tauchen (1986), we approximate the process of labor productivity x_t with the first-order Markov chain $\Pi_{x,x'}$ defined over equidistance grid points $G^x = \{x^1, \cdots, x^{T_x}\}$, where the number of grid points $T_x = 41$, lower bound $n^1 = -4\sigma$, and upper bound $n^{T_x} = 4\sigma$.

$$\Pi_{x,x'} = \mathbb{P}(x_{t+1} = x' | x_t = x), \quad x', x \in G^x \tag{1.46}$$

Computational Algorithm

The following is a computational algorithm for the alternating-offer wage bargaining model. The one for the Nash wage bargaining model is similar.

Step0 Guess the initial solutions: $q_t^{(0)}$, $\zeta_t^{(0)}$, $J_t^{(0)}$, $w_t^{f(0)}$, $w_t^{h(0)}$, $J_{u,t}^{(0)}$, $J_{n,t}^{f(0)}$, $J_{n,t}^{h(0)}$

– Use the steady state values

Step1 For each $\Phi_t \in G^n \times G^x$, solve for values of $q_t^{(1)}$, $\zeta_t^{(1)}$, $J_t^{(1)}$, $w_t^{f(1)}$, $w_t^{h(1)}$, $J_{u,t}^{(1)}$, $J_{n,t}^{f(1)}$, $J_{n,t}^{h(1)}$ at time t using $q_{t+1}^{(0)}$, $\zeta_{t+1}^{(0)}$, $J_{t+1}^{(0)}$, $w_{t+1}^{f(0)}$, $w_{t+1}^{h(0)}$, $J_{u,t+1}^{(0)}$, $J_{n,t+1}^{f(0)}$, $J_{n,t+1}^{h(0)}$ as solutions at time $t+1$

– Assume the constraint is not binding: set $\zeta_t^{(1)} = 0$ and obtain $q_t^{(1)}$ with a non-linear solver

* Exclude q_t that yields a negative consumption by giving a large number to the difference between the left-hand and right-hand sides

$$\left(\frac{\kappa_t}{q_t^{(1)}}\right)\lambda_t^{(1)} = \mathbb{E}_t\left[\beta\lambda_{t+1}^{(0)}\left\{x_{t+1}h_{t+1}^{(0)} - w_{t+1}^{(0)}h_{t+1}^{(0)} + \left(\frac{\kappa_{t+1}}{q_{t+1}^{(0)}} - \zeta_{t+1}^{(0)}\right)(1-\phi)\right\}\right] \tag{1.47}$$

* Note we need to find h_t with a non-linear solver during the process of solving for q_t[34]

[34]With some combinations of q_t and h_t, $c_{n,t}$ becomes negative, collapsing the algorithm. Given n_t and q_t, we, therefore, set the lower-bound of h_t for the non-linear solver as follows.

$$h_t > \frac{\kappa_t u_t \left[\left(\frac{1}{q_t}\right)^{\iota} - 1\right]^{\frac{1}{\iota}}}{x_t n_t} \tag{1.48}$$

Given n_t, we also set the lower-bound of q_t for the non-linear solver, satisfying

$$x_t h_t n_t > \kappa_t u_t \left[\left(\frac{1}{q_t}\right)^{\iota} - 1\right]^{\frac{1}{\iota}} \tag{1.49}$$

Meanwhile, (1.50) has two solutions for h_t, given q_t and n_t. Because $U_{n,t}$ is lower (in fact, the lowest) at the larger solution, we select the smaller solution by setting the upper-bound of h_t that switches the value of LHS minus RHS of (1.50) from negative to positive.

$$(c_{n,t}^{-1/\psi} - \tau(1-1/\psi)c_{n,t}^{-1/\psi}h_t^{1+1/\chi})x_t = \tau(1+1/\chi)c_{n,t}^{1-1/\psi}h_t^{1/\chi} + \varphi h_t^{1/\chi} \tag{1.50}$$

$$c_{n,t} = \frac{x_t h_t n_t - \kappa_t \left(u_t \left[\left(\frac{1}{q_t}\right)^{\iota} - 1\right]^{\frac{1}{\iota}}\right)}{n_t + u_t\Big(1 - \tau(1-1/\psi)h_t^{1+1/\chi}\Big)^{-\psi}} \tag{1.51}$$

$$\frac{c_{u,t}}{c_{n,t}} = \Big(1 - \tau(1-1/\psi)h_t^{1+1/\chi}\Big)^{-\psi} \tag{1.52}$$

$$\lambda_t = c_{u,t}^{-1/\psi} = c_{n,t}^{-1/\psi} - \tau(1-1/\psi)c_{n,t}^{-1/\psi}h_t^{1+1/\chi} \tag{1.53}$$

- If $q_t^{(1)} >= 1$, then set $q_t^{(1)} = 1$ and $\zeta_t^{(1)} = \kappa_t \lambda_t^{(1)} - \mathbb{E}_t[\cdot]$ and
- Then obtain $J_t^{(1)}$, $w_t^{f(1)}$, $w_t^{h(1)}$, $J_{u,t}^{(1)}$, $J_{n,t}^{f(1)}$, $J_{n,t}^{h(1)}$

Step2 Check for convergence

- End if the solution functions converge:

  for all $X \in \{q, J, w^f, w^h, J_u, J_n^f, J_n^h\}$

$$\max_{\Phi} \left|1 - \frac{X^{(1)}(\Phi)}{X^{(0)}(\Phi)}\right| < \varepsilon \tag{1.54}$$

- Otherwise, update the solution functions, and go to Step 1

Step3 Check if the negotiation is agreeable for each $\Phi_t \in G^n \times G^x$ with the solutions

$$\frac{J_{n,t}^f}{\lambda_t} + \left\{x_t h_t - w_t^f h_t + \left(\frac{\kappa_t}{q_t} - \zeta_t\right)(1-\phi)\right\} > \frac{J_{u,t}}{\lambda_t} \tag{1.55}$$

Step4 Check if the bounds of the state space is not binding

Steady State

In the steady state, the nonnegative job vacancy condition never binds. If it binds, $v = 0$ and $\theta = 0$. Then $n = 0$ and $u = 1$. This corresponds $c_u = 0$ and thus $\lambda = \infty$, which is a contradiction. Note $x = 1$.

$$n = \frac{q\left[\left(\frac{1}{q}\right)^{\iota} - 1\right]^{\frac{1}{\iota}}}{\phi + q\left[\left(\frac{1}{q}\right)^{\iota} - 1\right]^{\frac{1}{\iota}}} \tag{1.56}$$

$$\theta = \frac{v}{u} \tag{1.57}$$

$$u = 1 - n \tag{1.58}$$

$$v = u\left[\left(\frac{1}{q}\right)^{\iota} - 1\right]^{\frac{1}{\iota}} \tag{1.59}$$

$$f = \theta q \tag{1.60}$$

$$J = nU^n + uU^u + \beta J \tag{1.61}$$

$$U^n = \frac{c_n^{1-1/\psi}}{1-1/\psi} - \tau c_n^{1-1/\psi} h^{1+1/\chi} - \varphi \frac{h^{1+1/\chi}}{1+1/\chi} \tag{1.62}$$

$$U^u = \frac{c_u^{1-1/\psi}}{1-1/\psi} \tag{1.63}$$

$$\frac{\kappa}{q} = \beta\left\{xh - wh + \left(\frac{\kappa}{q}\right)(1-\phi)\right\} \tag{1.64}$$

$$h = 1 \tag{1.65}$$

$$\frac{c_u}{c_n} = 0.795 \tag{1.66}$$

$$\tau = \frac{1 - \left(\frac{c_u}{c_n}\right)^{-1/\psi}}{(1-1/\psi)h^{1+1/\chi}} \tag{1.67}$$

$$c_n = \frac{xhn - \kappa\left(u\left[\left(\frac{1}{q}\right)^{\iota} - 1\right]^{\frac{1}{\iota}}\right)}{\left(n + u\left(1 - \tau(1-1/\psi)h^{1+1/\chi}\right)^{-\psi}\right)} \tag{1.68}$$

$$\varphi = \frac{(c_n^{-1/\psi} - \tau(1-1/\psi)c_n^{-1/\psi}h^{1+1/\chi})x - \tau(1+1/\chi)c_n^{1-1/\psi}h^{1/\chi}}{h^{1/\chi}} \tag{1.69}$$

$$\lambda = c_u^{-1/\psi} \tag{1.70}$$

Under the Nash wage bargaining,

$$w = \frac{1}{h}\left\{\omega\left[xh + \theta\kappa\right] + (1-\omega)\left[\eta - (c_u - c_n) + \left(\frac{U^u - U^n}{\lambda}\right)\right]\right\} \tag{1.71}$$

Under the alternating-offer wage bargaining,

$$\frac{J_u}{\lambda} = \frac{U^u}{\lambda} - c_u + \eta + \beta\left\{\frac{J_n^f}{\lambda}f + \frac{J_u}{\lambda}(1-f)\right\} \tag{1.72}$$

$$\frac{J_n^f}{\lambda} = \frac{U^n}{\lambda} - c_n + w^f h + \beta\left\{\frac{J_n^f}{\lambda}(1-\phi) + \frac{J_u}{\lambda}\phi\right\} \tag{1.73}$$

$$\frac{J_n^h}{\lambda} = \frac{U^n}{\lambda} - c_n + w^h h + \beta\left\{\frac{J_n^h}{\lambda}(1-\phi) + \frac{J_u}{\lambda}\phi\right\} \tag{1.74}$$

$$w^f = \frac{\left(1 - \frac{(1-\delta)\beta}{1-\beta(1-\phi-f)} + \frac{\beta(1-\phi-\delta f)}{1-\beta(1-\phi-f)}\right)\left[\eta - (c_u - c_n) + \left(\frac{U^u - U^n}{\lambda}\right)\right] + \frac{(1-\delta)\beta}{1-\beta(1-\phi)}w^h h}{\left(1 + \frac{(1-\delta)\beta^2 f}{[1-\beta(1-\phi)][1-\beta(1-\phi-f)]} + \frac{\beta(1-\phi-\delta f)}{1-\beta(1-\phi-f)}\right)h} \tag{1.75}$$

$$w^h = \frac{1}{h}\left[xh + (1-\phi)(1-\delta)\beta\left\{-\xi + \left(\frac{\kappa}{q}\right)\right\} - (1-\delta)\left\{-\xi + \left(\frac{\kappa}{q}\right)\right\}\right] \tag{1.76}$$

$$w = w^f \tag{1.77}$$

Chapter 2

Why is the Momentum Absent? - Stock Price Reaction to News in the Korean Stock Market

2.1 Introduction

The momentum has been the premier anomaly since Jegadeesh and Titman (1993, 2001) found that longing stocks with high return over the past months and shorting stocks with low return over the same period generate profits for the following year in the U.S. stock market. Many subsequent studies report that the profitability of the momentum strategy is also pervasive throughout the world(Rouwenhorst (1998); Griffin, Ji, and Martin (2003)). However, Korea is one important exception: Chui, Titman, and Wei (2003, 2010) find that Korea is among a few of countries that do not exhibit positive momentum profits. Similar results are reported by many Korean studies.[1]

While several studies debate sources of the momentum payoffs, some of them try to explain why the momentum is not found in those exceptional countries, most of which are in Asia. Chui, Titman, and Wei (2010) focus on cultural differences, using individualism index related to overconfidence and self-attribution bias. They find that countries with weaker individualism have lower momentum profits, and vice versa. On the contrary, Du, Huang, and Liao (2009) test the state-dependence of the momentum profits in the Taiwan stock market, which also does not have the momentum. They show that the DOWN markets are negatively correlated with momentum profits, and that the DOWN markets occur more frequently in

[1] See Kim and Byun (2011) for details

Taiwan than in the U.S. In addition, Taiwan also exhibits substantial profits of the momentum strategy in the UP market. Therefore, they argue that the magnitude of momentum profits depends on the state of the market, not on differences among investors' behaviors.

Major theories on the momentum argue more fundamentally that the momentum profits arise because investors react to public and private information differently. In Barberis, Shleifer, and Vishny (1998), investors are subject to conservatism and representativeness bias. So they mistakenly judge future company's performance based on the past stream of news. In Daniel, Hirshleifer, and Subrahmanyam (1998), investors suffer from overconfidence and self-attribution bias. Therefore, they overestimate precision of their own private information and downweight public signals. In contrast, Hong and Stein (1999)'s model generates the momentum without relying on behavioral biases. Instead, it considers two groups of investors, one of whom ignore new information and only react to price movement. To sum, all three models agree that investors' underreaction to new public information generates the momentum. However, they make different assumptions on investors' response to public and private signals.

In this point of view, Chan (2003)'s results shed light on how investors react to public news. He documents that stocks with public news exhibit the momentum in the U.S stock market, but stocks without news do not. Specifically, Stocks with low returns during months when firms have news headlines show strong negative return drift thereafter. However, stocks with high returns and news headline drift less. Meanwhile, stocks without public news experience reversal after extreme price movements. These reversal and drift effects are concentrated among smaller, more illiquid stocks. If we assume that stocks with high price movement and public news have public information, these results imply that investors slowly respond to public information, but overreact to price shocks. With these results, Chan (2003) concludes that his findings generally support Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999).

This paper adds to this line of research by investigating why the moment is absent in the Korean stock market with comprehensive Korean news data. In this paper, we examine post holding period return patterns after extreme price movements with and without accompanying news headlines in the Korean stock market. First of all, we compute the momentum profits by building zero-investment portfolios that buy high performers and short low performers. And we confirm that no positive post holding returns exist for all stocks. However, stocks with news headlines have significantly positive momentum profits around a year after news. This implies that the momentum is closely associated with how investors respond to public and private information on firms, as argued by major models on the momentum. Further, we examine the size and B/M adjusted returns in each leg of the long-short portfolios. We find that the momentum profits of news stocks are induced mainly by return drift of bad performers (losers) with news. But good performers (winners) with news, as well as those without news, show significant reversal after news. This result is opposite to those of Chan (2003). This difference explains why Korea doesn't have the momentum effect in its stock market. These results are robust with the sample without illiquid stocks priced under 1,000 KRW.

The asymmetric reaction of stock prices to public news depending on return performance is not considered by the major theories on the momentum mentioned above. However, there are two possible explanations for this phenomenon. Hong, Lim, and Stein (2000) argue that "Bad news travels slowly", since managers have an incentive to slowly reveal bad information on their firms. This hidden information problem can cause drift of losers with news. Transactional frictions are also culprits. For instance, short sale constraint can impede investors from selling bad performers. To see the validity of these hypotheses, we separate stocks by firm size, and perform the same analysis. As a result, we find that there is no post-news drift of news losers in the largest group. It is not compatible with the fact that managers in big firms also have incentives to conceal bad news. Particularly, drift of news winners in the largest group excludes alternative explanation that large firms enjoy better media's attraction and analyst coverage. Meanwhile, news losers in the smallest group are found to drive most of drift after news in the entire set of news losers, which is the same as in the U.S stock market. Since small firms suffer from trading obstacles more, this result supports the role of transactional frictions on the momentum profits.

To verify whether transactional frictions are related to the positive momentum profits, we split the sample stocks further by monthly share turnover. The intuition is that the higher turnover the sample stocks have, the more transaction costs they have. From this analysis, we find that high turnover losers with news have statistically significant drift in their post holding returns, while those without news do not. As a result, only high turnover news stocks have the positive momentum profits. These findings support that transactional frictions play a role in the momentum effect.

The remainder of the paper is organized as follows. Section 2.2 describes the quick review of the methodology used in this paper. Section 2.3 discusses the properties of news data. Section 2.4 and Section 2.5 present the main empirical results on stock price reactions to public news. Section 2.6 derives further implications from the baseline results. Section 2.7 concludes

2.2 Methodology

To analyze what patterns stock prices show after public news, we perform several event studies. This section briefly explains event portfolio formation and test procedure that those event studies share in common. More details will be mentioned in the following relevant sections.

2.2.1 Event portfolio formation

Events are defined in two dimensions: news stocks vs no-news stocks, and winners vs losers. For the first dimension, we define news stocks as firms with one or more news headlines in each month. And we classify firms without any news in the same month as no-news stocks. This simple definition of news and no-news stocks is free of the selection bias, which might happen in separating stocks with more complicated form of public information.

For another dimension, we split firms by performance each month. We first rank news stocks based on their monthly stock returns, and then pick the top third and the bottom third as winners and losers, respectively. In the ranking, we consider only stocks that are traded in each month. To divide no-news stocks into winners and losers, we use the breakpoints of news stocks. It is because we want to analyze differences between new stocks and no-news stocks in the same standard. As a result, we build four event portfolios: "news winners", "news losers", "no-news winners", and "no-news losers". In this sense, we can interpret that this paper differentiates between good news and bad news with investors' reactions to news, instead of personal judgment on news content. Meanwhile, we also choose winners and losers from all stocks. In this case, we use their own breakpoints in the ranking procedure to check whether the momentum is really absent.

Note that no-news stocks play a important role as a benchmark for analyzing news stocks in this paper. Fama (1998) points out that a spurious abnormal return generated by a bad model can be statistically significant in long-run time horizon. However, if news and no-news stocks are all contaminated by a bad model problem in the same way, we can analyze how news occurrence affects stock return patterns, using their differences.

2.2.2 Test procedure

Our test procedure follows Chan (2003), which is based on Jegadeesh and Titman (1993) and Fama (1998).

For each event, we form equally weighted portfolio of stocks, and then calculate the calendar-time overlapping portfolio returns.[2] we use cumulative, instead of averaged, returns to capture how portfolios perform over time after formation. To be specific, suppose that we want to examine how well news winners perform over the subsequent four months. For calendar month t, we calculate abnormal returns of all stocks. And we then average t's abnormal returns across the last month's news winners. For the same calendar month t, we also average t's abnormal returns across stocks that were news winners two month ago. With the same procedure, we get t's

[2]The calendar-time overlapping portfolio method has been widely adopted in the financial literature. Fama (1998) recommends this approach to mitigate the cross-sectional dependence problem.

abnormal returns of $t-3$ and $t-4$'s news winner portfolios. Finally, we sum four t's returns of the $t-1$ to $t-4$ overlapping portfolios. We repeat this process for every calendar month to get a time-series of abnormal returns.

The above approach is different from standard momentum researches, because it uses only one month horizon to form event portfolios. However, it is consistent with Jegadeesh and Titman (1993), in a sense that overlapping portfolios are constructed to increase the power of test. Furthermore, it is unclear how to incorporate one month news data to multi-months overlapping portfolio formation. For example, it is not sure how to weigh news over six to twelve months. In particular, Chan (2003) repeats the same analysis by building six-month rolling-portfolios, and dividing them into news and no-news stocks by the last month news incidence. And he gets the same results

2.3 Data and Descriptive Statistics

Our sample consists of all companies listed on two Korean stock markets, KOSPI and KOSDAQ, between January, 2001 and December, 2010. Many studies focus on the KOSPI, which contains mainly large stocks. However, we include KOSDAQ stocks, because strong drifts after news is mainly seen in smaller stocks in Chan (2003). Also, we want to eliminate the sample bias, since large stocks usually enjoy better information dissemination.

We use the number of newspaper articles about a stock as a proxy for public information. We do not consider analyst reports and investment letters, because they are not available to broad audience. And we also discard articles from magazines, since we cannot figure out the exact time when information is released.

We search the Naver News Service for articles published in major Korean newspapers. The Naver News Service is one of the most comprehensive news data service in Korea. And it also provides convenient search criteria to find articles relevant to the sample stocks. To overcome data omission in small newspapers, we focus on the top five daily newspapers with nationwide circulation: Chosun Ilbo, Dong-a Ilbo, Joongang Daily, MK Business News, and Hankyung. These five newspapers account for 77.8% market share in daily circulation among total 17 daily nationwide newspapers in Korea.[3] So our news data are still a reasonable proxy for public information.

For each month, we obtain the number of news articles that mention firm's name in headline, not in the main body. Also, we collect articles categorized into the business and economics section in order to enhance news relevance further. We consider all changes of company's name during

[3]According to the Korea Audit Bureau of Circulations, Chosun Ilbo, Dong-a Ilbo, Joongang Daily, MK Business News, and Hankyung had 1.8, 1.3, 1.2, 0.9 and 0.5 million daily publication copies in 2010, respectively. Total daily circulation of all nationwide newspapers was 7.4 million in the same year.

the sample period in the search, using the disclosure data from the Korea Exchange(KRX). Most of these company names are commonly used in newspapers. But, for chaebols (conglomerates), the holding company names are also widely used for the subsidiaries. In this paper, we use only the subsidiary names, because it is hard to clarify which subsidiary is related to the specific news without reading the content. And we do not count news on the subsidiary as news on its holding company. These classifications possibly weaken our results, even though the simple definition of news stocks mitigate it.

We do not use the number of articles as a weight in our analysis. Instead we just classify firms with one or more news into news stocks in each month. It is because the number of news is positively correlated to firm's size.[4] Moreover, the amount of information in a given month does not equal to the number of articles, since there can be multiple news on the same subject. Our news data collection is a little different from Chan (2003)'s. He obtains news articles that mention stocks not only in headline, but also in lead paragraph. Also, he collects the number of dates when there was news on stocks, not the number of news articles.

We obtain all other data, such as stock return, market capitalization and book value of assets, from the Fn-Dataguide database. We also calculate monthly share turnover by dividing total trading shares by average of

[4]See Table 2.1, Panel B for details

total shares in a given month. Note that the sample do not contain stocks that suffer from unusual prices caused by abnormal trading features, such as trading suspension.

Panel A of Table 2.1 provides the number of stocks by news count at the end of each year. Improvement of media coverage seems to be limited; stocks with 5 or more news has reduced, while no-news stocks has increased. Cross-sectionally, stocks with no news account for about 50%. Only 10% of sample stocks have 5 or more news on average in a month.

In Table 2.1, Panel B, we calculate time-series average of monthly cross-sectional correlations between news count and firm's characteristics. Firm's size has strongly positive correlation with news incidence. This suggests that larger firms enjoy better news coverage. On contrary, stock returns and turnover are weakly related to news occurrence. It means that many stocks with extreme returns or high turnover are not featured in newspapers. Or, not all news change stock prices nor trigger trading more.

Panel C of Table 2.1 reports how frequently stocks have news on their lifespan. Over 60% of stocks have news during 25% to 75% of all periods in which they existed in the sample. 11% of stocks are featured in news over 90% over their existence. And only 2% of stocks have news during less 10% of their life span. News coverage on stocks is similar to the U.S. in Chan (2003), though 8% of firms have news during 10% or less of lifespan

Table 2.1: Summary statistics of news data

This table presents summary statistics of news observations from 2001 to 2010. Panel A lists the number of KOSPI and KOSDAQ stocks by news count for each December. News stocks refer to those that had one or more news headlines each month. Otherwise, stocks are categorized to no-news stocks. Cross-sectional proportions of each category are in parentheses. The last row averages the number of stocks in each category for all months. Panel B averages monthly Pearson cross-sectional correlations between the number of news and stock's characteristics: market value, return, and turnover. Panel C shows distribution of stocks by percents of months in which stocks had news headlines over their existence

Panel A : Number of Stocks

Year	Total stocks	No news stocks		News stocks: 4 or fewer news		News stocks: 5 or more news	
2001	1,271	404	(31.8)	458	(36.0)	409	(32.2)
2002	1,434	567	(39.5)	647	(45.1)	220	(15.3)
2003	1,478	859	(58.1)	478	(32.3)	141	(9.5)
2004	1,479	860	(58.1)	476	(32.2)	143	(9.7)
2005	1,491	858	(57.5)	508	(34.1)	125	(8.4)
2006	1,566	1,004	(64.1)	477	(30.5)	85	(5.4)
2007	1,599	816	(51.0)	627	(39.2)	156	(9.8)
2008	1,629	991	(60.8)	493	(30.3)	145	(8.9)
2009	1,660	822	(49.5)	679	(40.9)	159	(9.6)
2010	1,691	972	(57.5)	537	(31.8)	182	(10.8)
Avg	1,505	809	(53.8)	524	(34.8)	172	(11.4)

Panel B : Time series average of monthly Pearson cross-sectional correlation between news count and selected statistics

	Market value	Return	Turnover
Average	0.601	0.025	0.014
Standard Deviation	0.111	0.044	0.041

Panel C : Distribution of stocks by percent of months of having news over stocks' life

% of months over life	100-75%	(100-90%)	75-50%	50-25%	25-0%	(10-0%)
Proportion of stocks	0.18	(0.11)	0.24	0.40	0.18	(0.02)

in the U.S., which is much higher than in Korea.

Table 2.2 presents number of stocks, average market values and monthly returns for winners and losers at the end of each year. Even though we use different breakpoints for monthly performance, the number of all stocks roughly equals to sum of news and no-news stocks for both winners and losers in Panel A. Interestingly, winners tends to be bigger than losers in Panel B. Also news stocks is larger than no-news stocks, which again confirms that the number of news articles has strongly relation to firm's size. Meanwhile, news and no-news stocks show similar average monthly returns. It is also consistent with the weak correlation between news count and stock returns in Table 2.1, Panel C.

If a single industry dominates in each event portfolio, any return patterns in our analysis could be a disguised industry effect. So we categorize all stocks into 10 industries by the Fn-Dataguide's classification. And we then calculate the cross-sectional Herfindahl index of each event portfolio in each month. The Herfindahl index is calculated as $\sum_{i=1}^{10} S_{it}^2$, where S_{it}^2 is the percentage of stocks in industry i in t month. So, it represents the monthly industrial concentration in each portfolio. The time-series average of the Herfindahl indexes in four portfolios are 0.183$\sim$0.200, which are similar to 0.175 in all stocks. Thus news data are not highly biased toward some industries.

Transition probability of news and no-news stocks indicates that news

Table 2.2: Summary of winner and loser portfolios

This table presents summary statistics of winner and loser portfolios from 2001 to 2010. KOSPI and KOSDAQ stocks are divided into news stocks and no-news stocks according to whether they had one or more news headlines in each month or not. And then each category is subdivided into winners and losers. Winners denote stocks whose returns are higher than or equal to the top third in each month. On the contrary, losers are stocks whose returns are below or equal to the bottom third. Total stocks and news stocks are divided into winners and losers by their own breakpoints. However, for no-news stocks, the breakpoints of news stocks are used . All figures are the year-end except the last row, which averages the number of stocks for all months. Panel A counts stocks for each category. Panel B shows the cross-sectional average of market values for each category. Panel C reports the cross-sectional average of monthly returns.

	Panel A : Number of stocks						*Panel B : Average market value(billion KRW)*						*Panel C : Average monthly return(%)*					
	Losers			Winners			Losers			Winners			Losers			Winners		
Year	All	News	No-news	All	News	No-news	All	News	No-news	All	News	No-news	All	News	No-news	All	News	No-news
2001	420	287	134	420	287	101	42.3	52.0	21.7	387.9	499.8	165.6	-14.0	-14.2	-13.5	16.5	18.7	14.0
2002	474	287	194	474	287	181	197.0	306.8	29.8	174.1	246.2	64.0	-25.2	-25.3	-24.7	3.2	4.5	1.3
2003	488	205	333	488	205	186	110.6	575.6	30.4	265.7	493.0	41.9	-11.8	-12.1	-10.0	19.3	23.8	20.5
2004	489	205	316	489	205	208	176.6	347.0	57.8	237.9	346.3	41.3	-9.7	-9.7	-8.9	22.5	28.4	21.8
2005	493	209	340	493	209	217	88.2	170.7	105.2	850.9	1,823.5	106.4	-17.5	-15.6	-16.7	24.0	27.4	26.2
2006	517	186	407	517	186	256	108.0	225.4	85.0	651.3	1,375.0	197.5	-14.8	-16.1	-12.5	13.7	16.5	15.0
2007	528	259	239	528	259	232	374.1	569.6	151.1	703.8	1,135.7	109.0	-14.2	-15.5	-13.9	14.1	15.2	14.3
2008	538	211	427	538	211	282	390.0	979.6	69.7	263.8	364.0	146.4	-9.4	-8.4	-7.1	31.1	34.6	30.9
2009	548	277	292	548	277	215	414.2	757.4	100.8	469.6	813.5	102.3	-5.9	-7.1	-4.1	27.8	31.6	26.9
2010	559	238	413	559	238	195	206.4	530.9	82.0	1,246.8	2,359.4	260.8	-7.9	-7.7	-6.3	17.7	20.0	21.6
Average	498	230	287	498	230	212	281.3	537.4	80.9	461.3	756.1	117.8	-13.7	-14.5	-12.1	19.3	22.7	18.8

citation is a persistence phenomenon. About 60% of news stocks continue to have news in the next month. And 70% of no-news stocks are still ignored by newspapers in the subsequent month. However, transition matrix across four event portfolios shows that the average proportion of stocks in each portfolio switching into the same group over the subsequent month is roughly equal to the proportion into another group in the same return dimension(news winners vs news losers, or no-news winers vs no-news losers). Also transition probabilities into four portfolios are all less than 25%. Therefore, it implies that appearance of the events is not highly autocorrelated

2.4 Profitability of the momentum strategy

This section examines the momentum profits in the Korean stock market. We form long-short portfolios for all stocks, news stocks, and no-news stocks. And we compute returns in the subsequent months on zero investment portfolios, which buy winners and sell losers with equal weight. Table 2.3, Panel A reports cumulative returns of the long-short strategies after formation month up to two years. The first column of Panel A confirms that there is no positive profit of the momentum strategy for the entire set of stocks. Especially, the momentum profits for the first two months are negative. However, stocks with news headline show different results. The momentum strategies with news stocks returns around 4% from the

10th to the 14th month at 5% significance level. Moreover, these positive returns are not eliminated thereafter, albeit statistically insignificant. On the contrary, post holding period returns of no-news stocks are meaningfully negative during the first four months. The above results support the conjecture that the momentum effect is closely related to how investors react to public news.

In the first month, news stocks present negative long-short returns as no-news stocks. These return patterns may be caused by short-run micro-structure movements, such as bid-ask bounce. Therefore, we skip one month after portfolio formation before investing in the strategy, following the previous studies.[5] Panel B of Table 2.3 indicates that this procedure removes significance of loss in the first month for news stocks, as well as for no-news stocks. Also, the zero investment strategies with news stocks becomes more profitable for longer period. And negative returns from the momentum strategy with no-news stocks become smaller and insignificant. However, the positive long-short returns from all stocks are still statistically insignificant. In sum, eliminating the micro-structure effect strengthens the results in Panel A.

To see whether the results in Table 2.3 are driven by illiquid stocks, we rebuild the event portfolios without stocks priced below 1,000 KRW, and

[5]Chan (2003) waits a week between portfolio formation and investment. However, we skip longer period, since we want to test whether the micro-structure effect offsets positive momentum profits in the Korean stock market. Also one month gap is more standard in the literatures

Table 2.3: Cumulative long-short portfolio returns(%) at different holding periods

This table shows cumulative returns of long-short portfolios over several holding periods using the sample from 2001 to 2010. We categorize stocks into three groups : All stocks, news stocks that had at least one news during a month, and no-news stocks without any news. For each group, we subdivide stocks into two subgroups by their monthly performances : winners whose returns are higher than or equal to the top third, and losers whose returns are less than or equal to the bottom third. We calculate the calender-time overlapping portfolio returns for winner and loser portfolios, respectively. The monthly rolling portfolio returns are summed to get cumulative returns. And we then get zero-investment portfolio returns by buying winners and shorting losers. Panel A lists equally-weighted average cumulative returns and t-statistics by investing immediately after portfolio formation. And panel B reports results of the same analysis by waiting one month after formation before investing.

Months after	*Panel A : Immediate investment after formation*						*Panel B : Skipping one month after formation*					
portfolio	All stocks		News stocks		No-news stocks		All stocks		News stocks		No-news stocks	
formation	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat
1	-1.16	-3.23	-0.84	-2.03	-1.61	-4.33	-0.50	-1.51	-0.35	-0.91	-0.49	-1.43
2	-1.61	-2.70	-1.14	-1.71	-2.00	-3.35	-0.09	-0.17	0.20	0.35	-0.36	-0.71
3	-1.25	-1.64	-0.65	-0.77	-1.93	-2.64	0.15	0.23	0.50	0.68	-0.12	-0.20
4	-0.96	-1.09	-0.28	-0.29	-1.66	-2.01	0.46	0.59	1.03	1.12	-0.05	-0.07
5	-0.59	-0.59	0.28	0.25	-1.55	-1.68	0.69	0.74	1.48	1.37	0.06	0.07
6	-0.41	-0.36	0.67	0.53	-1.43	-1.43	0.77	0.70	1.91	1.57	-0.46	-0.47
7	-0.36	-0.28	1.09	0.77	-2.01	-1.76	0.56	0.46	1.86	1.38	-0.85	-0.76
8	-0.63	-0.45	0.96	0.63	-2.48	-1.97	1.26	0.97	3.00	2.12	-0.52	-0.46
9	-0.04	-0.02	2.00	1.26	-2.23	-1.77	2.06	1.51	4.02	2.75	0.04	0.04
10	0.92	0.61	3.14	1.96	-1.50	-1.16	2.58	1.79	4.73	3.10	0.62	0.50
11	1.51	0.96	3.95	2.37	-0.86	-0.65	2.92	1.86	5.14	3.07	0.84	0.63
12	1.81	1.07	4.31	2.38	-0.64	-0.45	2.85	1.65	5.21	2.86	0.71	0.49
13	1.70	0.92	4.32	2.21	-0.78	-0.50	2.74	1.50	4.96	2.59	0.89	0.58
14	1.53	0.79	4.00	1.97	-0.65	-0.40	2.71	1.37	4.85	2.34	0.90	0.55
15	1.52	0.73	3.90	1.79	-0.59	-0.34	2.52	1.21	4.79	2.19	0.50	0.29
16	1.38	0.63	3.88	1.69	-0.93	-0.52	2.21	1.02	4.77	2.10	-0.17	-0.10
18	0.88	0.37	3.89	1.56	-1.97	-1.00	2.23	0.94	4.94	1.98	-0.31	-0.16
20	1.30	0.51	3.94	1.45	-1.24	-0.61	2.09	0.83	4.79	1.81	-0.44	-0.22
22	1.42	0.51	4.67	1.63	-1.72	-0.79	2.18	0.78	4.82	1.69	-0.44	-0.20
24	1.33	0.45	4.24	1.39	-1.49	-0.64	2.70	0.89	5.74	1.85	-0.35	-0.15

repeat the same analysis as before. By excluding low priced stocks, we lose 12.7% of the sample stocks in average. As a result, average market value of the event portfolios increases by 6%$\sim$17%. Table 2.4 shows essentially the same results to the previous. However, the momentum profits from news stocks become smaller and shorter. It implies that transactional frictions are among contributors to the momentum effect.

2.5 Sources for non-existence of the momentum

To find why the momentum does not exist in the Korean stocks market, this section investigates drift and reversal in each leg of long-short strategies after events.

2.5.1 Abnormal returns in the event portfolios

Table 2.5 investigates long(winners) and short(losers) legs of the zero investment portfolios separately. For this, we adjust returns of each leg by controlling for size and book to market value(B/M), following Fama and French (1993). To be specific, for June of each year t, we sort all KOSPI and KOSDAQ stocks in the sample by size and B/M, and then calculate quintiles, respectively. For size sort, market value is measured at the end of June in year t. And for B/M sort, we use market value at the end of December in year $t-1$, and book value of common equity for the fiscal year ending in year $t-1$. Using the 5×5 breakpoints, we allocate stocks into 25 portfolios, and get equally-weighted monthly returns on each benchmark

Table 2.4: Cumulative long-short portfolio returns(%) without stocks under 1,000 KRW

This table shows cumulative returns of long-short portfolios over several holding periods using the sample without stocks under 1,000 KRW from 2001 to 2010. After eliminating stocks under 1,000 KRW, we categorize stocks into three groups : All stocks, news stocks that had at least one news during a month, and no-news stocks without any news. As Table 2.5, we subdivide stocks of each group into two subgroups by their monthly performances : winners whose returns are higher than or equal to the top third, and losers whose returns are less than or equal to the bottom third. We calculate the calender-time overlapping portfolio returns for winner and loser portfolios, respectively. The monthly rolling portfolio returns are summed to get cumulative returns. And we then get zero-investment portfolio returns by buying winners and shorting losers. Panel A lists equally-weighted average cumulative returns and t-statistics by investing immediately after portfolio formation. And panel B reports results of the same analysis by waiting one month after formation before investing.

Months after	*Panel A : Immediate investment after formation*						*Panel B : Skipping one month after formation*					
portfolio	All stocks		News stocks		No-news stocks		All stocks		News stocks		No-news stocks	
formation	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat
1	-1.01	-2.68	-0.79	-1.88	-1.26	-3.17	-0.50	-1.44	-0.46	-1.17	-0.44	-1.18
2	-1.46	-2.35	-1.21	-1.78	-1.60	-2.59	-0.03	-0.05	0.21	0.36	-0.18	-0.33
3	-1.04	-1.32	-0.60	-0.70	-1.39	-1.90	0.18	0.26	0.61	0.81	-0.05	-0.08
4	-0.78	-0.85	-0.13	-0.13	-1.22	-1.48	0.36	0.44	1.06	1.17	-0.20	-0.27
5	-0.54	-0.51	0.37	0.32	-1.33	-1.41	0.52	0.54	1.36	1.27	-0.22	-0.26
6	-0.41	-0.35	0.61	0.47	-1.33	-1.31	0.51	0.44	1.49	1.22	-0.69	-0.67
7	-0.46	-0.35	0.73	0.51	-1.89	-1.65	0.30	0.23	1.42	1.02	-1.15	-1.02
8	-0.74	-0.52	0.57	0.37	-2.44	-1.96	0.89	0.66	2.45	1.65	-0.96	-0.82
9	-0.25	-0.17	1.49	0.91	-2.33	-1.88	1.63	1.17	3.57	2.37	-0.80	-0.66
10	0.64	0.43	2.74	1.67	-2.02	-1.58	2.14	1.45	4.33	2.78	-0.18	-0.14
11	1.22	0.77	3.60	2.13	-1.36	-1.02	2.45	1.53	4.70	2.76	0.11	0.08
12	1.48	0.86	3.91	2.14	-1.07	-0.73	2.41	1.40	4.57	2.48	0.34	0.23
13	1.40	0.76	3.74	1.89	-0.88	-0.57	2.10	1.13	4.18	2.12	0.46	0.29
14	1.02	0.52	3.28	1.58	-0.83	-0.51	2.02	1.01	4.04	1.93	0.51	0.30
15	0.97	0.46	3.15	1.43	-0.72	-0.41	1.54	0.72	3.60	1.61	-0.18	-0.10
16	0.52	0.23	2.73	1.17	-1.38	-0.75	1.11	0.50	3.36	1.47	-1.05	-0.57
18	-0.07	-0.03	2.52	1.00	-2.30	-1.15	0.93	0.38	3.34	1.32	-0.97	-0.48
20	-0.07	-0.03	2.12	0.77	-1.85	-0.88	0.50	0.19	2.77	1.03	-1.36	-0.65
22	-0.12	-0.04	2.49	0.85	-2.44	-1.09	0.44	0.15	2.54	0.86	-1.39	-0.60
24	-0.44	-0.14	1.76	0.56	-2.14	-0.91	0.73	0.24	3.01	0.94	-1.17	-0.49

portfolio from July of t to June of $t + 1$.

At the end of June, we pick only stocks from our sample that match those in these 25 portfolios. With this procedure, we lose 21% of observations because of the merging criteria. In details, the sample stocks are required to have observations from the previous year as well as each June. Also, we remove financial and foreign stocks, as Fama and French (1993).

Finally, we obtain abnormal returns of each stock by subtracting the size and B/M matching portfolio returns each month. And we repeat the same analysis with these adjusted return as Section 2.4. Note that we skip one month after portfolio formation before investment to alleviate the micro-structure effects. Also, we rebuild four event portfolios based on the abnormal returns to see investors' reaction to idiosyncratic information, following the previous literature.[6]

In Table 2.5 Panel C, differences in abnormal returns between winners and losers show similar patterns to the long-short portfolio returns in Table 2.3. News stocks return significant profits from the tenth month, while no-news stocks have negative returns during the first to the ninth month. Overall, news incidence causes statistically meaningful difference.

[6]Chan (2003) primarily reports abnormal returns of the event portfolios formed by ranking on raw returns. But he also repeats the same analysis by ranking on adjusted returns, and shows that both approaches generate the same results

In Panel A and B, each leg of the long-short portfolios with news stocks and no-news stocks reveals more interesting results. For news stocks, winners see their abnormal returns reverse up to the ninth month. On the contrary, losers show meaningful drift from the third month. Therefore, buying news winners reduces positive momentum profits induced by shorting news losers. If we assume that high return stocks with news has good public news and vice versa, these results suggest that investors overreact to good news and underreact to bad news in Korea.

We find different results in legs from no-news stocks. No-news winners present weak reversal in their abnormal returns, which is significant only in the first month. But no-news losers show stronger reversal during almost all subsequent months. As a result, differences in post holding period returns between winners and losers for no-news stocks are negative.

Differences in excess returns between news losers and no-news losers are statistically significant for all time periods. Moreover, they are much bigger than those from winners. Therefore, it confirms that return drift of news losers drives the positive momentum profits in news stocks.

To verify sources of non-existence of the momentum in Korea, we compare the above results with the U.S. in Chan (2003). And we find that key differences between two countries are in news winners and no-news winners. In the U.S. stock market, news winners have weak positive post holding period returns. In addition, no-news winners show significant post-

Table 2.5: Cumulative abnormal return(%) at various horizons, waiting one month before investment

This table shows cumulative abnormal returns of winner and loser portfolios over several holding periods using the sample from 2001 to 2010. We get abnormal returns by controlling for size and B/M, following Fama and French (1993). We categorize stocks into news and no-news stocks. And then, we subdivide each group into winners and losers by the monthly abnormal returns. For performance breakpoints, we use the top third and the bottom third of monthly abnormal returns of news stocks as before. We skip one month after formation, and calculate the calender-time overlapping portfolio abnormal returns for winner and loser portfolios. The monthly rolling portfolio returns are summed to get cumulative returns. Panel A and Panel B list the results for winner and loser portfolios, respectively. And Panel C shows differences between two portfolios

Months after	News stocks		No-news stocks		Difference	
portfolio formation	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat
Panel A : Winner portfolio						
Formation month	20.85	47.27	17.05	43.10	3.81	15.69
1	-0.54	-2.91	-0.36	-1.99	-0.18	-0.85
3	-1.12	-3.39	-0.40	-1.20	-0.72	-1.92
6	-1.57	-3.04	-0.72	-1.45	-0.85	-1.40
9	-1.56	-2.25	-0.53	-0.91	-1.03	-1.30
12	-1.47	-1.77	-0.22	-0.31	-1.25	-1.21
15	-1.64	-1.73	-0.78	-0.99	-0.86	-0.69
18	-1.61	-1.56	-1.10	-1.12	-0.52	-0.36
24	-1.15	-0.88	-0.57	-0.48	-0.58	-0.31
Panel B : Loser portfolio						
Formation month	-15.33	-78.48	-13.96	-65.78	-1.37	-12.66
1	-0.10	-0.53	0.49	2.87	-0.59	-2.70
3	-0.82	-2.11	0.75	2.88	-1.57	-4.14
6	-1.99	-3.13	1.43	3.77	-3.41	-6.16
9	-3.11	-3.70	1.69	3.24	-4.80	-6.67
12	-4.41	-4.47	1.38	2.21	-5.79	-6.02
15	-4.34	-3.66	1.38	1.88	-5.72	-4.88
18	-4.48	-3.20	1.88	2.20	-6.35	-4.68
24	-6.37	-3.48	1.21	1.08	-7.57	-4.23
Panel C : Winner-loser						
1	-0.43	-1.31	-0.85	-2.70	0.42	1.28
3	-0.30	-0.51	-1.14	-2.20	0.84	1.60
6	0.42	0.46	-2.15	-2.86	2.57	3.48
9	1.55	1.37	-2.21	-2.51	3.76	4.47
12	2.94	2.32	-1.60	-1.67	4.54	4.28
15	2.70	1.90	-2.16	-2.02	4.85	3.92
18	2.86	1.80	-2.97	-2.27	5.83	4.21
24	5.21	2.75	-1.78	-1.13	6.99	4.40

news drift in their returns. These results are exactly opposite to those in the Korean stock market. Therefore, we conclude that overreaction in news winners and no-news winners are the main reasons for the momentum's absent in Korea.

To exclude the effects from illiquid stocks, we also perform the same analysis without stocks priced below 1,000 KRW. Table 2.6 shows generally the same results to Table 2.5. For news stocks, return reversal in winners are significant up to the fifth month, albeit weaker. Also, losers still present returns drift. As a result, positive difference in post holding period returns between winners and losers from news stocks become larger than before. For no-news stocks, return drift in winners become significantly stronger. Meanwhile, positive post holding period returns in losers become insignificant and reverse after the ninth month. As a result, we still have negative differences in post holding period returns between winners and losers from no-news stocks. Differences in excess returns between news losers and no-news losers are less significant. On the contrary, those between news winners and no-news winners become larger.

Chan (2003) also perform similar analysis without stocks under $5 among the U.S. stocks, and reports the same results as with those illiquid stocks. But he provides only statistics of differences between winners and losers. Therefore, we cannot compare the above results in the Korean stock market in detail with the U.S. However, it is obvious that return reversals

Table 2.6: Cumulative abnormal return(%) without stocks under 1,000 KRW, waiting one month before investment

This table shows cumulative abnormal returns of winner and loser portfolios over several holding periods using the sample without stocks under 1,000 KRW from 2001 to 2010. After eliminating stocks under 1,000 KRW from the sample, we get abnormal returns by controlling for size and B/M, following Fama and French (1993). We categorize stocks into news and no-news stocks. And then, we subdivide each group into winners and losers by the monthly abnormal returns. For performance breakpoints, we use the top third and the bottom third of monthly abnormal returns of news stocks as before. We skip one month after formation, and calculate the calender-time overlapping portfolio abnormal returns for winner and loser portfolios. The monthly rolling portfolio returns are summed to get cumulative returns. Panel A and Panel B list the results for winner and loser portfolios, respectively. And Panel C shows differences between two portfolios

Months after	News stocks		No-news stocks		Difference	
portfolio formation	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat
Panel A : Winner portfolio						
Formation month	20.87	46.78	17.35	45.00	3.52	13.08
1	-0.40	-2.12	-0.45	-2.33	0.04	0.19
3	-0.73	-2.10	-0.87	-2.62	0.15	0.36
6	-0.97	-1.82	-1.85	-3.55	0.88	1.40
9	-0.39	-0.53	-2.42	-3.68	2.03	2.19
12	0.45	0.47	-2.61	-3.11	3.06	2.43
15	0.37	0.34	-3.58	-3.95	3.95	2.72
18	0.40	0.32	-4.61	-4.09	5.01	2.96
24	0.81	0.56	-5.24	-3.61	6.05	2.82
Panel B : Loser portfolio						
Formation month	-15.07	-75.94	-14.16	-61.71	-0.91	-7.83
1	0.02	0.11	0.31	1.72	-0.29	-1.30
3	-0.38	-0.98	0.41	1.45	-0.78	-1.97
6	-1.03	-1.61	0.16	0.38	-1.19	-1.93
9	-1.67	-1.92	-0.09	-0.18	-1.58	-1.74
12	-2.58	-2.46	-1.33	-1.93	-1.26	-1.07
15	-2.52	-1.97	-2.03	-2.55	-0.49	-0.35
18	-2.63	-1.82	-2.93	-3.03	0.30	0.19
24	-3.98	-2.08	-4.84	-3.57	0.86	0.39
Panel C : Winner-loser						
1	-0.42	-1.31	-0.76	-2.31	0.33	0.99
3	-0.35	-0.59	-1.28	-2.51	0.93	1.81
6	0.06	0.06	-2.01	-2.62	2.07	3.00
9	1.28	1.12	-2.33	-2.70	3.61	3.95
12	3.03	2.37	-1.28	-1.29	4.31	3.70
15	2.90	1.95	-1.55	-1.48	4.45	3.22
18	3.02	1.86	-1.68	-1.25	4.70	3.02
24	4.79	2.48	-0.39	-0.27	5.18	2.94

in news winners and no-news winners hamper the momentum effect in the Korean stock market.

To test the robustness of long horizon return patterns in Table 2.5, we perform two further analyses in the appendix. First, we repeat the same analysis with the buy and hold abnormal returns, considering controversial debates on the calendar-time overlapping portfolio return and the buy and hold return. The evidence in Table 2.9 is not different from the result in Table 2.5. Second, we examine performance of the event portfolios in two separate time periods, 2001 to 2005 and 2006 to 2010. Even though two sub-periods are too short to get reliable statistics, we can find qualitatively similar return patterns to those in Table 2.5.

2.5.2 Discussion

What does the above baseline results in the Korean stocks market imply on the major theories on the momentum? In fact, stocks with or without news in this analysis are not clearly linked to those with private or public information in these theories. For example, public news can be considered as public information. But we can also think that private information includes news articles that some investors read. Similarly, return movements of no-news stocks can be thought to be induced by investors' private information. But they may be caused by momentum traders who react only to price shocks. Nevertheless, any connection to these models fails to explain that investors overreact to good news, but underreact to bad news in Korea, which is not found in the U.S. It is because these theories assume that investors show symmetric response to information regardless of news content. After all, these models are designed to capture the momentum effect, which is not found in Korea. Therefore, none of these theories seem to explains the big picture. Chan (2003) also points out that none of three models justify differences in degree of returns drift or reversal between winners and losers, even though his results on the U.S. stock market generally support the ideas of these models.

Then, what other hypotheses can explain the asymmetric reaction of stock price to news? Regarding this question, Hong, Lim, and Stein (2000) proposes that “Bad news travels slowly”. In their analysis, stocks with low analyst coverage react more sluggishly to bad news than good news. They interpret this result as follows; if managers prefer higher stock prices, they will actively disclose good information to the public, but they hesitate to reveal bad information. If managers slowly diffuse bad information via newspapers, news losers will have drift in their returns and vice versa. This interpretation is consistent with the basic findings in this paper.

Another possible explanation is the role of transactional frictions. Information on firms are thought to be incorporated into stock prices via trading activities. However, if trading obstacles, such as short sale constraint, impede investors from trading on bad news, then losers will drive drift after news. Chan (2003) reports that underreaction after news is mainly found in small and illiquid stocks, and also argues that transactional frictions are possible causes of the momentum.

2.6 Implications of asymmetric reaction of stock price to news

This section investigates what asymmetric reaction of stock price to news implies. Particularly, we focus on examining two possible explanations for this phenomenon: manager's incentive to reveal bad information slowly, and transactional frictions.

2.6.1 Stock price, news and firm's size

Any manager has incentive to disclose good news quickly but diffuse bad news slowly. Therefore, bad news travels slowly regardless of firm's size. We anticipate that large stocks also should present significant differences between news winners and news losers. In this sense, we examine how news incidence affects post-news return patterns differently depending on firm's size. At the end of each June, we separate the sample stocks into five size groups by the size breakpoints from the previous analysis. We then repeat the same analysis for each group as in Table 2.5. Note that we use the size and B/M matching portfolio returns from the previous analysis to compute abnormal returns for each group.

In Table 2.7, news losers in the largest quintile (size 5) do not see significant drift in their post-holding returns. It is not compatible with the

Table 2.7: Cumulative abnormal returns(%) by size quintiles, waiting one month before investment

This table shows cumulative abnormal returns of winner and loser portfolios by five size quintiles using the sample from 2001 to 2010. We get abnormal returns by controlling for size and B/M, following Fama and French (1993). We categorize stocks into news and no-new stocks, and also split them into five size quintiles. And then, we subdivide each group into winners and losers by the monthly abnormal returns. For performance breakpoints, we use the top third and the bottom third of monthly abnormal returns of news stocks, as before. We skip one month after formation, and calculate the calender-time overlapping portfolio abnormal returns for each portfolio. The monthly rolling portfolio returns are summed to get cumulative returns. Size 5 refers to the largest quintile, while size 1 denotes the smallest quintile. The time-series average of stock count in each portfolio is in parenthesis.

Months after	Winner portfolio						Loser portfolio						Winner-loser					
portfolio	News stocks		No-news stocks		Difference		News stocks		No-news stocks		Difference		News stocks		No-news stocks		Difference	
formation	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat
Size 5(large)	(61)		(19)				(56)		(27)				(117)		(44)			
formation	14.18	47.80	13.39	34.16	0.79	2.28	-11.98	-53.99	-11.80	-49.64	-0.19	-1.32	-	-	-	-	-	-
1	0.27	1.16	-0.50	-1.38	0.77	2.02	0.15	0.67	-0.03	-0.08	0.19	0.43	0.12	0.28	-0.47	-0.82	0.59	1.15
3	1.32	3.00	-0.63	-0.91	1.95	2.39	-0.17	-0.36	-1.26	-1.86	1.09	1.47	1.49	1.89	0.63	0.69	0.86	1.04
6	1.93	2.75	-0.54	-0.50	2.47	1.95	-0.05	-0.06	-1.49	-1.30	1.44	1.19	1.97	1.61	0.95	0.65	1.02	0.94
9	2.85	2.86	-0.64	-0.47	3.49	2.02	0.38	0.39	-2.42	-1.57	2.80	1.66	2.48	1.61	1.78	1.05	0.69	0.51
12	4.02	3.26	-1.15	-0.68	5.17	2.43	0.18	0.16	-2.79	-1.52	2.97	1.37	3.83	2.15	1.63	0.84	2.20	1.26
15	5.09	3.30	-2.44	-1.21	7.53	2.84	1.06	0.80	-3.31	-1.60	4.37	1.78	4.03	1.94	0.87	0.39	3.16	1.56
18	6.67	3.70	-2.35	-0.98	9.02	2.92	2.15	1.42	-3.54	-1.56	5.69	2.01	4.52	2.00	1.19	0.49	3.33	1.52
21	8.08	3.80	-1.99	-0.72	10.07	2.78	3.53	2.03	-3.11	-1.19	6.64	1.99	4.55	1.85	1.12	0.42	3.43	1.46
24	9.50	3.83	-1.53	-0.49	11.03	2.65	4.24	2.11	-3.74	-1.27	7.97	2.02	5.26	1.96	2.21	0.84	3.06	1.19
Size 4	(41)		(38)				(40)		(51)				(80)		(87)			
formation	18.69	35.55	15.61	33.25	3.07	8.48	-13.99	-54.95	-12.79	-50.07	-1.20	-6.64	-	-	-	-	-	-
1	-0.20	-0.81	-0.46	-1.72	0.27	0.81	-0.04	-0.14	0.18	0.69	-0.22	-0.58	-0.16	-0.36	-0.64	-1.56	0.48	1.01
3	-0.18	-0.39	-0.58	-0.99	0.40	0.59	-0.33	-0.63	-0.26	-0.50	-0.07	-0.10	0.15	0.20	-0.32	-0.36	0.46	0.52
6	0.62	0.83	0.09	0.09	0.53	0.44	-0.75	-0.85	0.23	0.31	-1.01	-0.96	1.37	1.15	-0.48	-0.38	1.80	1.35
9	1.01	1.03	0.82	0.63	0.18	0.13	-1.07	-0.83	0.32	0.30	-1.32	-0.84	2.08	1.28	0.24	0.16	1.77	1.03
12	1.67	1.27	2.38	1.52	-0.71	-0.37	-2.08	-1.34	1.87	1.22	-3.94	-1.82	3.75	2.18	0.52	0.27	3.23	1.48
15	1.90	1.17	2.35	1.42	-0.46	-0.20	-1.77	-0.93	2.35	1.44	-4.13	-1.62	3.67	1.75	0.00	0.00	3.67	1.51
18	2.42	1.25	4.32	2.15	-1.74	-0.66	-1.03	-0.48	2.77	1.52	-3.84	-1.37	3.45	1.49	1.14	0.52	2.40	1.02
21	3.58	1.54	5.01	2.25	-1.54	-0.52	0.58	0.22	3.85	1.89	-2.82	-0.87	3.00	1.11	1.26	0.60	2.10	0.87
24	6.48	2.58	7.24	2.83	-0.24	-0.07	0.49	0.17	3.39	1.43	-2.90	-0.78	5.99	2.17	3.80	1.80	2.34	0.78

(Continued)

Months after	Winner portfolio						Loser portfolio						Winner-loser					
portfolio	News stocks		No-news stocks		Difference		News stocks		No-news stocks		Difference		News stocks		No-news stocks		Difference	
formation	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat	avg(%)	t-stat
Size 3	(33)		(44)				(34)		(61)				(67)		(102)			
formation	22.15	28.77	16.76	32.04	5.39	9.16	-15.74	-54.89	-13.73	-47.10	-2.01	-10.16	-	-	-	-	-	-
1	-0.45	-1.52	0.03	0.13	-0.48	-1.19	0.01	0.03	-0.18	-0.71	0.20	0.42	-0.46	-0.87	0.22	0.50	-0.68	-1.07
3	-0.43	-0.67	0.36	0.68	-0.80	-0.85	-0.32	-0.40	-0.70	-1.59	0.38	0.41	-0.11	-0.11	1.07	1.42	-1.18	-0.89
6	-0.88	-0.97	-0.02	-0.03	-0.86	-0.69	-1.89	-1.62	-1.06	-1.43	-0.82	-0.65	1.01	0.75	1.04	1.06	-0.03	-0.02
9	-1.70	-1.20	1.45	1.15	-3.15	-1.81	-3.89	-2.62	-0.84	-0.78	-3.05	-1.91	2.20	1.41	2.30	1.60	-0.10	-0.06
12	-1.88	-1.07	2.51	1.43	-4.38	-1.93	-5.57	-2.65	-0.86	-0.64	-4.71	-2.21	3.69	1.94	3.36	1.80	0.33	0.15
15	-2.02	-0.95	1.17	0.61	-3.19	-1.20	-5.82	-2.32	-1.34	-0.84	-4.49	-1.75	3.81	1.68	2.51	1.16	1.30	0.47
18	-1.60	-0.65	1.39	0.60	-3.22	-1.03	-5.47	-1.81	-1.86	-0.97	-3.61	-1.17	3.87	1.45	3.74	1.58	0.22	0.07
21	-2.45	-0.84	2.72	1.09	-5.33	-1.46	-7.02	-1.89	-2.18	-1.00	-4.29	-1.10	4.27	1.28	4.76	1.91	-0.93	-0.22
24	-3.61	-1.10	2.46	0.82	-6.58	-1.62	-6.54	-1.60	-0.36	-0.14	-6.03	-1.32	2.50	0.67	2.79	0.89	-1.34	-0.27
Size 2	(30)		(45)				(32)		(69)				(62)		(112)			
formation	25.81	23.28	17.82	30.62	8.00	8.33	-16.96	-44.16	-14.74	-44.07	-2.22	-8.91	-	-	-	-	-	-
1	-1.25	-3.00	0.21	0.69	-1.46	-2.57	-0.93	-2.21	0.50	1.64	-1.43	-2.60	-0.32	-0.54	-0.29	-0.60	-0.03	-0.04
3	-2.19	-2.64	0.98	1.82	-3.17	-3.12	-3.63	-4.16	1.10	2.04	-4.73	-4.27	1.45	1.36	-0.12	-0.15	1.56	1.33
6	-3.81	-2.95	0.93	1.19	-4.75	-3.02	-5.34	-4.18	2.00	2.28	-7.33	-4.45	1.52	0.92	-1.06	-0.88	2.59	1.28
9	-2.67	-1.72	-0.78	-0.67	-1.89	-0.99	-3.38	-1.62	2.15	1.85	-5.53	-2.89	0.71	0.28	-2.93	-1.74	3.64	1.51
12	-2.63	-1.29	-0.75	-0.49	-1.87	-0.75	-3.28	-1.12	2.69	1.89	-5.98	-2.21	0.66	0.20	-3.45	-1.79	4.10	1.37
15	-2.57	-1.03	1.60	0.79	-4.17	-1.29	-4.32	-1.23	2.10	1.22	-6.42	-1.92	1.76	0.48	-0.49	-0.26	2.25	0.58
18	-0.41	-0.13	2.22	0.82	-2.63	-0.66	-2.77	-0.62	2.68	1.18	-5.46	-1.39	2.36	0.52	-0.47	-0.21	2.83	0.60
21	-1.05	-0.29	3.15	1.01	-4.20	-0.99	-5.22	-1.07	3.12	1.13	-8.34	-1.98	4.17	0.87	0.03	0.01	4.14	0.78
24	0.86	0.20	6.12	1.59	-5.38	-1.17	-5.08	-0.88	3.64	1.06	-8.88	-1.74	5.82	1.09	2.32	0.83	3.50	0.61
Size 1	(30)		(53)				(35)		(82)				(64)		(131)			
formation	32.36	27.68	21.20	26.49	11.15	11.97	-21.63	-50.95	-18.05	-49.70	-3.59	-13.38	-	-	-	-	-	-
1	-2.08	-3.65	-0.48	-1.27	-1.60	-2.20	-1.82	-3.28	0.54	1.33	-2.36	-3.42	-0.26	-0.31	-1.02	-1.63	0.76	0.75
3	-4.50	-4.42	-0.63	-0.85	-3.87	-2.88	-3.26	-2.87	1.60	2.05	-4.86	-3.43	-1.24	-0.79	-2.23	-1.85	0.99	0.51
6	-7.59	-5.57	0.26	0.22	-7.85	-4.09	-5.84	-3.65	2.26	2.03	-8.10	-4.29	-1.75	-0.96	-2.00	-1.16	0.25	0.10
9	-11.24	-5.98	0.40	0.26	-11.64	-4.59	-8.85	-3.93	4.68	2.81	-13.53	-4.74	-2.39	-1.04	-4.28	-1.91	1.89	0.60
12	-12.54	-5.13	0.48	0.27	-13.02	-4.47	-10.13	-3.45	6.75	3.42	-16.88	-5.21	-2.41	-0.77	-6.27	-2.43	3.86	1.12
15	-14.42	-5.58	0.45	0.23	-14.88	-4.73	-12.03	-3.21	7.42	3.31	-19.45	-4.71	-2.39	-0.67	-6.96	-2.51	4.57	1.19
18	-16.46	-5.02	0.97	0.43	-17.43	-4.64	-13.53	-3.16	8.55	3.26	-22.08	-4.73	-2.93	-0.67	-7.58	-2.56	4.65	0.98
21	-16.55	-4.24	2.11	0.75	-18.65	-4.14	-12.67	-2.67	9.23	2.95	-21.90	-4.26	-3.87	-0.83	-7.12	-2.04	3.25	0.66
24	-19.48	-3.98	3.92	1.19	-23.40	-4.20	-18.19	-3.47	7.53	2.20	-25.72	-4.28	-1.30	-0.26	-3.61	-1.07	2.31	0.39

conjecture that managers in large firm also have incentive to reveal bad information slowly. In fact, information about large firms gets out more quickly, since they enjoy more news media's attention and wider analyst coverage.[7] However, this explanation is not consistent with significant drift in post-news returns of news winners among the largest stocks.

Meanwhile, we can see that news losers in the smallest quintile continue to lose money in the subsequent periods, which mostly drive the drift found in the entire set of news losers. This result confirms Chan (2003)'s argument that transactional frictions play a role in creating the positive momentum profits since small stocks are more vulnerable to them. In contrast to news losers, news winners in the smallest quintile present large reversal after news. As a result, differences in post news returns between winners and losers in the smallest news stocks are significantly negative. It is exactly opposite to Chan (2003)'s results on the U.S. stock market[8], in which the smallest news stocks have positive returns of the momentum strategy. In sum, large reversal of small news winners after news drives out the momentum in Korea.

[7]Hong, Lim, and Stein (2000) argue that sluggish diffusion of news from small firms is caused by fixed costs of information acquisition. That is, investors put more effort to learning about large stocks that take large position because of transactional frictions.

[8]For this analysis, Chan (2003) redefines news stocks as firms that experienced both a headline and high share turnover. This procedure is a remedy to increase the number of no-news stocks in the largest quintile. However, we do not use this more restrictive definition of news stocks since it can undermine consistency of the analysis

2.6.2 Stock price, news, and share turnover

From the previous analysis, we already see that the role of transactional frictions on the momentum profits is plausible. To confirm whether trading obstacles contribute to drift of news losers, we conduct a further experiment with a proxy representing stocks with large transactional frictions, high turnover stocks. Since high share turnover needs more transaction costs, we conjecture that there should be distinctions between high turnover news stocks and low turnover news stocks.

We separate news stocks into high turnover group and low turnover group by the median monthly share turnover of the entire set of stocks. Then we subdivide each group into winners and losers as before. Table 2.8 Panel A calculates post-news return patterns for each category. Note that we use the same size and B/M adjusted returns as Section 2.5 for the analysis. In Panel B, we also get results for no-news stocks as a benchmark with the same procedure. We subdivide no-news stocks into winners and losers with the breakpoints of news stocks, as before.

First of all, we find that both of news stocks and no-news stocks share negative post holding period returns in high turnover group and positive returns in low turnover group. These results are consistent with Lee and Swaminathan (2000), who report that firms with high past turnover ratios earn lower future returns and vice versa. However, there is one distinction; high turnover news losers show statistically significant reversal, while those

Table 2.8: Cumulative abnormal returns(%) by monthly share turnover, waiting one month before investment

This table shows cumulative abnormal returns of winner and loser portfolios by monthly share turnover using the sample from 2001 to 2010. We get abnormal returns by controlling for size and B/M, following Fama and French (1993). We categorize stocks into news and no-news stocks, and also split them into high and low turnover stocks. For the latter, we use the median of monthly share turnover of the entire set of stocks as a breakpoint. And then, we subdivide each group into winners and losers by the monthly abnormal returns. For performance breakpoints, we use the top third and the bottom third of monthly abnormal returns of news stocks as before. We skip one month after formation, and calculate the calender-time overlapping portfolio abnormal returns for each portfolio. Panel A and Panel B report results for news stocks and no-news stocks, respectively. The time-series average of stock count in each portfolio is are in parenthesis.

Panel A : news stocks						
Months after	High Turonver		Low Turonver		Difference	
portfolio formation	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat
Winner portfolio	(58)		(27)			
Formation month	29.62	33.21	17.54	26.40	12.08	21.00
1	-1.28	-3.97	0.64	1.48	-1.93	-3.86
3	-3.75	-6.25	1.84	1.99	-5.59	-4.74
6	-5.55	-5.78	3.70	2.43	-9.26	-4.45
9	-6.78	-5.15	4.41	2.13	-11.19	-3.81
12	-7.19	-4.17	6.67	2.55	-13.86	-3.62
15	-8.00	-3.93	7.36	2.30	-15.36	-3.37
24	-10.02	-3.25	10.82	2.48	-20.84	-3.17
Loser portfolio	(58)		(30)			
Formation month	-19.62	-72.60	-14.81	-53.80	-4.81	-21.11
1	-0.98	-2.54	0.78	2.00	-1.77	-3.08
3	-3.02	-3.65	2.52	3.11	-5.54	-4.21
6	-6.78	-4.94	3.56	3.18	-10.34	-5.06
9	-9.34	-4.81	2.09	1.45	-11.43	-3.97
12	-12.17	-4.94	2.56	1.38	-14.74	-4.17
15	-13.48	-4.48	3.83	1.77	-17.31	-4.07
24	-20.73	-4.81	7.01	2.41	-27.74	-4.70
Winner-loser						
1	-0.30	-0.56	-0.14	-0.23	-0.16	-0.24
3	-0.74	-0.75	-0.68	-0.65	-0.05	-0.04
6	1.23	0.90	0.15	0.10	1.08	0.64
9	2.56	1.45	2.32	1.29	0.24	0.12
12	4.98	2.28	4.11	1.81	0.87	0.37
15	5.48	2.19	3.53	1.29	1.95	0.69
24	10.71	3.38	3.81	1.09	6.90	1.77

(Continued)

Panel B : no-news stocks						
Months after	High Turonver		Low Turonver		Difference	
portfolio formation	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat
Winner portfolio	(52)		(43)			
Formation month	24.68	36.72	17.00	28.14	7.68	19.75
1	-1.25	-3.67	0.64	1.77	-1.89	-3.59
3	-2.01	-2.79	1.31	1.62	-3.31	-2.57
6	-3.71	-3.25	2.68	1.81	-6.39	-2.76
9	-3.93	-2.55	3.39	1.87	-7.32	-2.43
12	-4.78	-2.51	4.32	2.02	-9.10	-2.51
15	-5.32	-2.28	4.79	1.84	-10.10	-2.25
24	-7.57	-2.23	6.19	1.58	-13.76	-2.13
Loser portfolio	(65)		(73)			
Formation month	-18.43	-60.00	-14.34	-54.45	-4.09	-22.21
1	0.39	1.06	0.68	2.54	-0.28	-0.57
3	-0.19	-0.24	2.09	4.20	-2.28	-2.04
6	-1.05	-0.71	3.51	4.17	-4.56	-2.22
9	-0.52	-0.26	5.51	5.10	-6.03	-2.27
12	-1.84	-0.73	5.67	4.35	-7.51	-2.23
15	-2.24	-0.75	5.43	3.42	-7.68	-1.87
24	-5.13	-1.15	7.73	3.15	-12.86	-2.08
Winner-loser						
1	-1.64	-3.17	-0.04	-0.08	-1.61	-2.59
3	-1.82	-2.04	-0.78	-0.88	-1.03	-0.84
6	-2.65	-2.01	-0.83	-0.57	-1.82	-0.96
9	-3.41	-2.13	-2.12	-1.19	-1.29	-0.57
12	-2.94	-1.53	-1.34	-0.72	-1.59	-0.62
15	-3.07	-1.49	-0.65	-0.31	-2.42	-0.84
24	-2.44	-0.73	-1.54	-0.50	-0.90	-0.22

in high turnover no-news losers do not. As a results, only high turnover news stocks show significantly positive differences in post holding returns between winners and losers. Therefore, these results support the idea that transactional frictions are closely related to the momentum profits.

Chan (2003) uses high turnover news stocks as a proxy that have more influential news to stock prices.[9] And he argues that the momentum effect is caused by investors' reaction to public news highlighted by trading activities of other investors. We do not follow this alternative interpretation, since the results in Table 2.1 Panel C indicates that the relation between news counts and turnover is weak in Korea.

2.7 Conclusion

We investigate why the Korean stock market does not have the momentum effect by examining stock returns after news. (1) Even though there is no positive post holding returns in the entire set of stocks, stocks with news headline have the positive momentum profits. (2) Return drift of news stocks with bad performance mainly causes the positive long-short portfolio returns. However, Korea has the distinctive feature, which is opposite to the U.S.; return reversals of news winners and no-news winners restrain the momentum profits. (3) Further analyses with firm's size and share turnover reveal that the asymmetric response of stock price to public

[9] Chan (2003) defines high turnover stocks as those that had turnover in three days around news headlines that belongs to the top third of daily share turnover over three months before the formation month.

news is not caused by managers' incentive to reveal bad information on their firms slowly, but by transactional frictions.

There are some unexplored features in the findings of this paper. First, why do stocks with high return have reversal after public news in the Korean stock market, while those in the U.S. have drift in their post news returns? The most important difference between stock markets of two countries is their size; The U.S. has about three time more listed companies than Korea. Limited capacity of information problems, which restrict investors' attention or news coverage, might be severer in the U.S. than in Korea. Difference in market conditions, such as liquidity, can also be a culprit. The effect of market size on information diffusion and stock prices will be a valuable direction for future research.

Second, why do the largest news winners show drift, while the smallest ones present large reversals in their post-news returns?[10] It seems that investors react to public news differently depending on firm's size. For instance, transactional frictions have different effects on stock price by firm's size. Further analysis about the relation between investor's reaction to information by firm's size will be fruitful.

[10]Because Chan (2003) reports only differences in post holing returns between winners and losers in the size-split analysis, we cannot compare details between Korea and the U.S.

Appendix

Buy and Hold Return

The relative merits of the calendar-time portfolio returns(CTR) and the buy and hold return(BHR) are discussed controversially in the previous literatures. Particularly, Loughran and Ritter (2000) forcefully oppose the use of the calendar-time portfolio returns. Therefore, we conduct the same analysis as Table 2.5 with BHR. To get abnormal returns of each event portfolio, we calculate BHRs of all stocks up to two years, skipping one month after formation. And then we subtract BHR of the size and B/M matching portfolio over the same period. Finally we calculate equally weighted average of abnormal returns across stocks for each group. We repeat this process every month. Table 2.9 suggests that results are little changed. All legs of long-short portfolios for news and no-news stocks tend to have higher returns over horizons than those in Table 2.5. Also news stocks are more profitable. Differences between winners and losers are statistically significant over almost all periods.

Subperiod Analysis

We test long horizon abnormal returns of the event portfolios shown in Table 2.5 for two separate time periods, 2001 to 2005 and 2006 to 2010. Note that five years are too short to draw reliable statistics. For example, there are no completely non-overlapping two-year returns in five year

Table 2.9: Buy and holding average abnormal return(%), waiting one month before investment

This table shows buy and holding average abnormal returns of winner and loser portfolios over several holding periods using the sample from 2001 to 2010. We skip one month before investing, and calculate the buy and holding returns for each stocks. And we then get abnormal returns by subtracting buy and holding returns of the size and B/M matching portfolio over the same horizon. Finally, we calculate equally-weighted average of these abnormal returns across stocks in each event portfolios from 2.5. Panel A and Panel B list the results for winner and loser portfolios, respectively. And Panel C shows differences between two portfolios

Months after	News stocks		No-news stocks		Difference	
portfolio formation	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat
Panel A : Winner portfolio						
1	-0.62	-3.46	-0.26	-1.38	-0.35	-1.64
3	-1.36	-4.79	-0.29	-0.81	-1.07	-2.48
6	-2.03	-5.26	-0.60	-1.12	-1.43	-2.57
9	-2.64	-5.56	-0.80	-1.39	-1.84	-2.79
12	-2.97	-4.92	-1.45	-2.04	-1.52	-1.82
15	-4.09	-4.64	-1.48	-1.78	-2.60	-2.31
18	-5.37	-5.59	-2.22	-2.01	-3.15	-2.29
24	-6.08	-4.78	-3.15	-2.42	-2.93	-1.76
Panel B : Loser portfolio						
1	-0.32	-1.41	0.46	2.53	-0.77	-2.78
3	-1.60	-4.82	0.75	2.53	-2.35	-5.51
6	-3.49	-8.73	1.26	2.89	-4.75	-8.52
9	-5.21	-9.89	1.76	3.12	-6.97	-9.63
12	-6.29	-9.38	1.46	2.14	-7.75	-7.53
15	-6.90	-8.29	1.71	2.11	-8.61	-7.04
18	-7.44	-8.33	2.91	3.32	-10.35	-7.80
24	-8.79	-6.95	2.17	2.13	-10.96	-6.88
Panel C : Winner-loser						
1	-0.30	-0.90	-0.72	-2.22	0.42	1.17
3	0.25	0.50	-1.04	-1.87	1.28	2.16
6	1.46	2.21	-1.86	-2.10	3.32	3.69
9	2.57	3.31	-2.56	-2.64	5.13	5.10
12	3.32	3.39	-2.91	-2.43	6.23	4.29
15	2.82	2.03	-3.19	-2.19	6.01	3.23
18	2.07	1.48	-5.13	-3.00	7.20	3.54
24	2.71	1.37	-5.32	-2.71	8.03	3.56

sample period. Nevertheless, we perform the same analysis for each sample period. The evidence in Table 2.10 indicates that the performance of event portfolios in both subperiods are quite similar to 2.5. Even though positive post holding returns of news stocks are not statistically significant, differences in abnormal return between news and no-news stocks are meaningfully large. Interestingly, return patterns in the latter period become stronger than those in the earlier period. For news stocks, reversal of winners and drift of losers become larger. It implies that the recent development in information technologies, such as the Internet, is not likely to reduce investors' overreaction nor underreaction.

Table 2.10: Cumulative abnormal returns (%) for two sub-periods, waiting one month before investment

This table shows cumulative abnormal returns of winner and loser portfolios for two sub-periods: 2001∼2005 and 2006∼2010. We get abnormal returns by controlling for size and B/M, following Fama and French (1993). For each sub-period, we categorize stocks into news and no-news stocks. And then, we subdivide each group into winners and losers by the monthly abnormal returns. For performance breakpoints, we use the top third and the bottom third of monthly abnormal returns of news stocks as before. We skip one month after formation, and calculate the calender-time overlapping portfolio abnormal returns for winner and loser portfolios. The monthly rolling portfolio returns are summed to get cumulative returns. Panel A and Panel B present results for each sub-periods, respectively

Panel A : 2001-2005						
Months after	News stocks		No-news stocks		Difference	
portfolio formation	Avg(%)	t-stat	Avg(%)	t-stat	Avg(%)	t-stat
Winner portfolio						
Formation month	21.69	30.29	17.97	27.30	3.72	10.33
1	-0.42	-1.56	-0.51	-1.71	0.09	0.30
3	-0.79	-1.51	-0.27	-0.47	-0.52	-0.91
6	-0.80	-1.03	-0.36	-0.41	-0.44	-0.45
9	-0.83	-0.83	-0.70	-0.66	-0.14	-0.11
12	-0.57	-0.47	-0.64	-0.52	0.07	0.04
15	-0.08	-0.05	-1.82	-1.25	1.75	0.86
18	0.31	0.21	-1.95	-1.09	2.27	0.99
24	1.05	0.48	-1.40	-0.56	2.45	0.70
Loser portfolio						
Formation month	-15.62	-60.74	-14.55	-45.87	-1.07	-7.44
1	-0.08	-0.27	0.57	1.91	-0.65	-1.75
3	-0.96	-1.47	0.71	1.62	-1.67	-2.55
6	-2.17	-1.95	1.39	2.30	-3.57	-3.83
9	-2.24	-1.45	1.59	1.80	-3.83	-3.21
12	-3.19	-1.75	1.40	1.22	-4.58	-2.65
15	-2.12	-0.97	1.36	0.92	-3.48	-1.71
18	-1.43	-0.53	2.24	1.24	-3.66	-1.48
24	-3.27	-0.83	1.67	0.68	-4.94	-1.55
Winner-loser						
1	-0.34	-0.68	-1.08	-2.04	0.74	1.42
3	0.17	0.17	-0.98	-1.10	1.15	1.34
6	1.37	0.89	-1.76	-1.35	3.13	2.50
9	1.40	0.73	-2.29	-1.43	3.69	2.70
12	2.62	1.28	-2.03	-1.16	4.65	2.83
15	2.04	0.89	-3.19	-1.43	5.23	2.54
18	1.74	0.64	-4.19	-1.44	5.93	2.39
24	4.32	1.17	-3.07	-0.75	7.39	2.50

(Continued)

Panel B : 2006-2010 Months after portfolio formation	News stocks Avg(%)	t-stat	No-news stocks Avg(%)	t-stat	Difference Avg(%)	t-stat
Winner portfolio						
Formation month	20.10	38.45	16.22	36.78	3.88	11.77
1	-0.67	-2.59	-0.19	-0.85	-0.48	-1.65
3	-1.47	-3.22	-0.54	-1.35	-0.92	-1.71
6	-2.23	-2.95	-0.97	-1.62	-1.26	-1.50
9	-2.26	-2.07	-0.32	-0.44	-1.94	-1.61
12	-2.07	-1.53	0.04	0.04	-2.11	-1.31
15	-2.89	-1.87	0.32	0.31	-3.21	-1.73
18	-4.16	-2.58	-0.30	-0.22	-3.86	-1.81
24	-3.24	-1.73	0.10	0.06	-3.34	-1.17
Loser portfolio						
Formation month	-15.06	-52.33	-13.42	-49.97	-1.65	-10.77
1	-0.20	-0.78	0.40	2.04	-0.60	-2.25
3	-0.84	-1.73	0.74	2.28	-1.58	-3.51
6	-1.89	-2.34	1.32	2.43	-3.21	-4.35
9	-4.01	-3.72	1.47	2.01	-5.48	-5.34
12	-5.39	-4.01	0.61	0.71	-6.00	-4.47
15	-5.98	-3.51	0.65	0.72	-6.64	-3.76
18	-6.56	-3.22	1.05	0.94	-7.61	-3.67
24	-8.10	-2.73	0.08	0.05	-8.17	-2.53
Winner-loser						
1	-0.47	-1.03	-0.59	-1.55	0.12	0.29
3	-0.63	-0.81	-1.28	-2.01	0.66	0.96
6	-0.34	-0.28	-2.29	-2.39	1.95	2.04
9	1.75	1.07	-1.79	-1.61	3.54	2.89
12	3.32	1.70	-0.58	-0.47	3.89	2.44
15	3.09	1.36	-0.33	-0.29	3.43	1.83
18	2.39	0.96	-1.35	-0.96	3.75	1.83
24	4.85	1.63	0.02	0.01	4.83	1.90

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초 록

본 논문은 주식시장과 노동시장에 관한 두 가지 연구로 구성되어 있다. 첫 번째 연구에서는 노동공급이 노동시간 및 취업활동 모두를 통해 이루어지는 노동매칭모형에서 기간별 대체탄력성이 실업변동성에 미치는 영향에 관하여 분석하였다. 효용함수의 비선형성은 임금경로와 할인률경로를 통하여 실업변동성에 영향을 준다. 임금경로는 효용함수의 비선형성이 실업시 한계효용가치를 경기순응적으로 만들어 임금경직성에 영향을 미침을 의미한다. 실업시 한계효용가치는 한 명의 취업자가 실업자가 될 경우 가계가 얻는 추가적인 효용가치를 나타내며 크게 실업수당과 비노동시간의 한계효용가치로 구분된다. 효용함수가 비선형일 경우, 노동생산성 상승시 소비 및 노동시간은 증가하고 소비한계효용이 감소하기 때문에 가계는 취업자의 기여보다 실업자의 기여를 더 중요하게 여기게 된다. 따라서 경기확장시 비노동시간의 한계효용가치는 상승하게 되며, 실업수당의 비중이 상대적으로 낮기 때문에 실업시 한계효용가치도 경기순응적이 된다. 선행연구들은 실업시 한계효용가치가 고정되어 있다고 가정하고 임금경직성을 만들어 왔다. 효용함수의 비선형성은 임금경로를 통하여 이러한 임금경직성을 약화시켜 실업변동성을 감소시킨다.

할인률경로는 효용함수의 비선형성이 확률할인인자(stochastic discount factor)를 통하여 미래수익에 대한 할인률에 영향을 미침을 의미한다. 임금이 생산성 충격을 모두 흡수하지 않는다면 경기확장시 주가는 상승하게 된

다. 이는 더 높아진 기업의 미래수익이 더 낮아진 주식수익률로 할인되도록 만든다. 주식수익률 하락은 신규채용에 따른 기대수익을 높이기 때문에 기업이 채용활동에 더 많은 자원을 투자하도록 유인한다. 따라서 효용함수의 비선형성은 할인률경로를 통하여 실업변동성을 확대시킨다.

이와 같이 임금경로와 할인률경로는 그 효과가 상충되는데, 효용함수의 비선형성이 실업변동성에 미치는 전체 효과는 기간별 대체탄력성의 수준에 따라 결정된다. 기간별 대체탄력성이 낮을 경우 가계는 기간별 소비규모를 변화시키지 않으려 하기 때문에 소비의 가치를 비노동시간의 가치보다 더 중요하게 여기게 된다. 이는 실업시 한계효용가치의 경기순응성을 강화시킨다. 또한 소득효과가 강해지면서 기업은 일시적인 생산성 상승에도 채용을 확대하려고 하지 않게 된다. 특히 임금경직성 약화로 기업의 마진 변화폭이 축소되고 주식수익률 변동도 낮아지게 된다. 따라서 기간별 대체탄력성이 낮아지면 노동시장 변동성이 축소된다. 이와 반대로 기간별 대체탄력성이 높으면 기간별 소비평활화 욕구가 줄어들면서 소비한계효용의 경기역행성이 축소된다. 이는 실업시 한계효용가치의 경기순응성을 약화시킨다. 또한, 임금경직성이 높아져 주식수익률의 경기역행성은 높아진다. 특히 대체효과가 소득효과보다 우세하기 때문에 미래 소비를 위하여 채용투자를 늘리려는 유인이 증폭된다. 따라서 기간별 대체탄력성이 높아지면 노동시장 변동성이 높아지게 된다. 임금이 다기간협상(alternating-offer wage bargaining)을 통하여 이루어지는 노동매칭모형을 계량적으로 분석한 결과, 기간별 대체탄력성 계수값이 2.0일 경우 실제 통계자료 수준의 실업변동성이 생성되는 것으로 나타났다.

두 번째 연구에서는 우리나라 주식시장에서 뉴스에 대한 주가 반응을 분석하고 모멘텀 투자전략의 수익성에 대하여 살펴보았다. 선행연구의 실증결과와 동일하게 우리나라 주식시장에서는 모멘텀 투자전략이 양의 보유수익률을 보이지 못하였다. 그러나 뉴스에 보도된 주식들만으로 모멘텀 투자전략을 구성할 경우에는 보유 1년 후 유의한 수익을 얻을 수 있었다. 이러한 모멘텀 수익은 뉴스에 보도된 패자주식들(loser stocks)의 가격이 공매 이후에도 지속적으로 하락하기 때문에 발생하였다. 승자주식들(winner stocks)의 경우 뉴스보도 여부와 상관없이 가격역전으로 보유수익률이 음을 나타내어 미국주식시장과는 차이를 나타내었다. 이와 같이 승자주식들이 음의 보유수익률을 보이기 때문에 전체 주식들로 모멘텀 투자전략을 구성할 경우 유의한 수익을 얻지 못하는 것으로 나타났다.

뉴스보도 이후 승자주식들의 가격역전 현상과 패자주식들의 가격하락 지속 현상은 주가가 뉴스에 대하여 비대칭적으로 반응함을 시사한다. 기업규모별로 모멘텀 투자전략의 수익성을 분석한 결과, 대기업의 경우 뉴스에 보도된 패자주식들의 가격이 더 이상 하락하지 않은 반면 승자주식들의 가격은 지속적으로 상승하였다. 이는 뉴스에 대한 주가의 비대칭적 반응이 나쁜 뉴스는 천천히 퍼진다는 Hong and Stein (1999)의 가설로 설명되지 못함을 보여준다. 한편 거래비용에 크게 노출되는 소기업의 경우 뉴스에 보도된 패자주식들의 가격이 큰 폭의 하락을 지속하는 것으로 나타났다. 또한 기업투자자의 보유비율이 낮은 경우 뉴스에 보도된 패자주식들은 수익률 하락을 지속한 반면 기업투자자의 보유비율이 높은 경우에는 그렇지 않았다. 이러한 결과들은 공매제한 등 거래비용으로 주가가 뉴스에 대하여

비대칭적으로 반응할 수 있음을 보여준다. 마지막으로 기업의 미래성과에 대한 편견 정도를 나타내는 거래회전율을 기준으로 뉴스에 보도된 주식들을 나누어 모멘텀 수익을 살펴본 결과, 거래회전률이 높은 주식들이 거래회전률이 낮은 주식들보다 더 큰 폭의 수익률 하락을 나타내었다. 애널리스트들이 거래회전률이 높은 주식들의 미래성과를 과대 평가하는 경향이 있다는 점을 감안할 때 동 결과는 뉴스에 대한 주가의 비대칭적 반응이 투자자들의 편견에 의해서도 일어날 수 있음을 보여준다.

주요어: 기간간 대체탄력성, 실업변동성, 모멘텀, 뉴스

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