In the first chapter, I offer a structural DSGE framework to analyze the impact of stochastic information friction in explaining business cycles and asset prices. I document a new mechanism to generate time variation in uncertainty from the information channel, where rational agents’ beliefs from Bayesian learning features time-varying uncertainty in a stochastic imperfect information environment. Information uncertainty provides considerable explanatory power for business fluctuations and carries a negative price of risk for asset valuations. The interaction between imperfect information and financial market friction provides an important channel to amplify the effect of information uncertainty on asset pricing. Empirical evidence supports the model’s prediction of negatively priced information uncertainty risk. Firms with high exposure to information friction shock generate significantly lower returns than firms with low information friction shock exposure. A mimicking portfolio, IFS factor, generates 6% excess return per annum.

The second chapter documents the history of aggregate positions in U.S. index options and investigates the driving factors behind use of this class of derivatives. We construct several measures of the magnitude of the market and characterize their level, trend, and covariates. Measured in terms of volatility exposure, the market is economically small, but it embeds a significant latent exposure to large price changes. Out-of-the-money puts are the dominant component of open positions. Variation in options use is well described by a stochastic trend driven by equity market activity and a significant negative response to increases in risk. Using a rich collection of uncertainty proxies, we distinguish distinct responses to exogenous macroeconomic risk, risk aversion, differences of opinion, and disaster risk. The results are consistent with the view that the primary function of index options is the transfer of unspanned crash risk.

The third chapter uses social networks to identify information transfer in security markets. We focus on connections between mutual fund managers and investment banks via managers’ past working experience. We find mutual fund managers show significant stock picking skills on firms which are the long-term clients of the investment banks for which the managers formerly work. Managers perform significantly better on connected holdings relative to non-
connected holdings. A replicating portfolio of connected stocks outperforms a replicating portfolio of non-connected stocks by approximately 7.4% per annum. We also compare the stock performance before and after two network-break events (firm switching investment bank and Lehman’s collapse) and we find that managers’ stock picking skills disappear when connections break. The results are consistent with mutual fund managers gaining an informational advantage through the social networks.
To my parents, for their love and support.
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CHAPTER 1

STOCHASTIC INFORMATION FRICTION,
BUSINESS CYCLES AND ASSET PRICES

1.1 Introduction

Uncertainty and expectation play a central role in explaining business cycles and asset price fluctuations. Economic conditions are perturbed by various uncertainties; rational agents form expectations and make optimal decisions accordingly. A majority of macroeconomic and asset pricing researchers focus on the uncertainty part. Economists propose various types of shocks (to technology, investment, policy, etc.) to explain business cycles. However, the expectation part draws less attention from academia. Some progress has been made recently in the literature of imperfect information-driven business cycles, in which expectation errors occur because of imperfect information. In this paper, I explore the idea that time-varying imperfect information induces time variation in rational agents’ belief uncertainty – thus generating fluctuations in macroeconomic quantities and asset prices at business cycle frequencies.

Two recent works, Lorenzoni (2009) and Blanchard et al. (2013), have renewed attention to imperfect information and limited information processing as sources of expectational errors in a rational framework. The key story is: fundamental productivity is unobservable; agents learn it from noisy public signals and form rational beliefs. Thus, the presence of noisy signals generates expectation errors. In these papers, the noise level in the public signals is constant. It captures the information quality in the economy. In contrast to previous studies, I ask the questions: what if the information quality is time-varying and subject to uncertainty shock? Does information uncertainty affect business cycles or asset price dynamics? Intuitively, when information quality is bad, the signal extraction problem becomes less precise and agents’ beliefs become more uncertain. To better answer these questions, I conduct a structural analysis under a rational DSGE framework, and study the impact of time-varying information uncertainty on macroeconomic dynamics and asset prices.

The analysis is based on a standard real business cycle model with three main ingredients. First, I introduce both permanent and transitory productivity shocks. Agents observe the total productivity, but not the decomposition of the two parts. In addition to total produc-
tivity, agents have access to another noisy signal regarding the permanent component of the productivity. Second, I incorporate the time-varying information environment, by introducing Information Friction Shocks (IFS), which affect the noise level of the noisy signal that agents receive. Rational agents update their beliefs with Bayesian learning. The information friction shocks affect agents’ inference problems and generate time-varying belief uncertainty. Belief dispersion becomes wider when information friction is more severe. Third, I incorporate a reduced-form financial sector – exhibiting time-variant financial frictions – which is correlated with the information condition. Severe information imperfection induces higher financial friction, resulting in higher capital adjustment cost.

Information friction plays two roles in the model. The first role is to generate time-variant belief uncertainty through Bayesian learning. Deterioration in information quality induces more uncertainty in agents’ beliefs. The second role is to affect the allocation efficiency through interaction with financial market friction. Deterioration in information quality induces greater costs associated with information acquisition and greater capital adjustment costs. I calibrate the model to match the moments of key macroeconomic variables and asset returns. A positive information friction shock increases belief uncertainty. In response to this higher belief uncertainty, households consume less, invest more, and work more. Marginal utility of consumption responds positively to the information friction shock through interaction with the financial friction channel. The model predicts a negatively priced risk associated with information friction uncertainty.

To validate the model’s prediction, I explore the asset pricing implication empirically. First, I construct an empirical measure to proxy for information friction shocks. In the model, information friction is closely related to belief uncertainty of the current period’s productivity. Therefore, I use the Survey of Professional Forecasters data, and focus on the individual-level forecast of nominal GDP of the current quarter to construct the belief dispersion measure. Belief dispersion (\( BD \)) is defined as the 75 and 25 percentile differences in the logarithm of nominal GDP. To mitigate the concern that belief dispersion may be driven by fundamental macro uncertainty, I orthogonalize the time series of belief dispersion using estimates from Jurado et al. (2015) to control any effects from the fundamental uncertainty channel. The remaining orthogonalized part is defined as the proxy for information friction shocks (\( IFS \)).

With the empirical proxy for information friction shocks, I use Fama-French 25 size-value portfolios to test whether \( IFS \) is a priced risk factor. The results show a significant negative price of risk for these test assets. The classical Fama-French 3 factors model is able to explain the test portfolios’ returns with an \( R^2 \) of 70%. Adding the \( IFS \) factor into the Fama-French 3 factor model significantly improves the explanatory power of test assets’ returns, with an
$R^2$ increased from 70\% to 80\%. I also explore the cross-sectional return predictability using portfolio sorts methodology. My main finding is that exposure to information uncertainty risk strongly predicts future asset returns. Firms with high exposure to information friction shock generate significantly lower returns than firms with low information friction shock exposure. The estimated risk premium associated with information friction shock is negative and statistically significant. A long-short zero investment strategy earns a significant 55 bps excess return per month, or about 6.8\% per annum. All of these empirical findings are consistent with the model prediction of a negatively priced information uncertainty risk.

Since the seminal work of Bloom (2009), a large and growing body of literature has studied the effects of uncertainty shock in explaining macroeconomic dynamics. It is important to distinguish information uncertainty, which is the main interest of this paper, from fundamental uncertainty. The previous works on uncertainty shocks are usually studied in a perfect information environment. The uncertainty shock is typically defined as the conditional volatility of a disturbance to economic fundamentals. Agents are sure about the economic condition today, but are not sure about the volatility tomorrow. However, information uncertainty in this paper refers to the agents’ beliefs uncertainty about the economic condition today which features time-variant volatility, even when economic fundamentals do not exhibit second moment variations. One important message this article delivers is that time variation in uncertainty could be generated from two mechanisms. One is macro uncertainty from the fundamental channel; the other is information uncertainty from the information channel. To better understand the time-varying uncertainty from these two channels, I also analyze a DSGE model with both information friction shocks and uncertainty shocks. Both contribute to the explanation of macroeconomic quantities and asset prices. Both information uncertainty and fundamental uncertainty carry a negative price of risk. I find information uncertainty and fundamental uncertainty each contributes 50\% to the total uncertainty risk in the model.

Through the welfare analysis, I find high information friction harms social welfare. A policy implication is to reduce the information uncertainty. Increasing the quality of public news, increasing the accuracy of public reports, increasing transparency, and reducing policy uncertainty are all effective ways to reduce information uncertainty or costs associated with information acquisition in the economy. Reducing information friction enhances social welfare by increasing allocation efficiency.

**Related Literature** This paper is mainly related to three strands of the literature: 1) expectational error driven business cycles, 2) the literature that aims to explain the joint behavior of macroeconomic dynamics and asset prices, and 3) uncertainty shocks.
First, this paper contributes to the expectational error driven business cycles literature. The idea that imperfect information can cause sluggish adjustment in economic variables and generate fluctuation driven by expectational errors goes back, at least, to Lucas (1972). More recently, Blanchard et al. (2013) and Boz et al. (2011) have renewed attention to imperfect information and limited information processing as sources of expectational errors in a rational framework. Along this direction, there is also some progress in asset pricing literature featuring imperfect information with rational learning, such as Ai (2010). In all of these models, the economy features a constant level of information imperfection. The noisy signal about the unobservable has a constant noise level. In contrast to these papers, I allow the noise level to be time-varying, thus inducing time-variant beliefs uncertainty. To my knowledge, this paper is the first to incorporate a time-variant information environment with Bayesian learning into the DSGE model to study the effects of time-varying expectational errors.

Second, this paper contributes to a growing body of literature on macroeconomic asset pricing models that aims to jointly explain macroeconomic quantities and asset prices. The starting point of this literature goes back to Jermann (1998) and Tallarini (2000). Some recent progress includes work by Croce (2014) and Papanikolaou (2011). Croce (2014) considers a one-sector stochastic growth model with Epstein-Zin preferences and examines the long-run productivity risk. Papanikolaou (2011) considers a multi-sector model and explores the cross-sectional risk premia from investment-specific technology shocks. In contrast to their studies, I focus on the implications of information friction shocks risk premium. I also incorporate financial friction shocks into the model. The interaction between information friction and financial friction provides a promising and considerable explanation power for both macroeconomic quantities and asset valuation fluctuations.

Third, this paper also contributes to the vast literature on uncertainty shocks. The effects of uncertainty shocks have been widely studied in business cycles and asset pricing, e.g. Bloom (2009) and Bansal et al. (2014). These works are usually studied in a perfect information environment. The uncertainty shocks from these works come from the perturbation of economic fundamentals. One novelty of this paper is that I am able to distinguish between information uncertainty and fundamental uncertainty in an economy featuring imperfect information. The information uncertainty comes from the imperfect information channel via Bayesian learning; it doesn’t depend on economic fundamentals. One important message this article delivers is that time variation in uncertainty could be generated from two mechanisms. Both contribute to explain macroeconomic quantities and asset prices.

The remainder of the paper is organized as follows: Section 2 presents the model; Section 3 solves the Bayesian learning problem; Section 4 presents the model solutions and illustrates...
the main mechanism; Section 5 investigates the asset pricing implication from the model, followed by the empirical evidence in Section 6; Section 7 presents the analysis of a model with both information and fundamental uncertainty shocks; Section 8 offers some concluding remarks.

1.2 A Model with Stochastic Information Friction

Production

There is one representative firm in the economy. The production takes a standard Cobb-Douglas form, with capital $K_t$ and labor $L_t$ as inputs

$$Y_t = (A_t L_t)^{1-\alpha} K_t^\alpha$$

where $Y_t$ is the output and $\alpha \in (0, 1)$ is the capital’s share of output. Notice that this specification ensures a balanced growth path, and $A_t^{1-\alpha}$ is the total factor productivity (TFP). There is a deterministic growth component $\Gamma_t$ in the productivity $A_t$.

$$A_t = \Gamma_t e^{\alpha t}$$

The term $\mu \equiv \log(\Gamma)$ represents the deterministic long run growth rate. The $a_t$ (in logs) represents the business cycle component of the productivity. Productivity $a_t$ has two components: the permanent component $x_t$ and the transitory component $z_t$.

$$a_t = x_t + z_t$$

The permanent component $x_t$ follows the unit root process. It builds up gradually with a series of "growth" shocks $g_t \equiv \Delta x_t$. In particular, $g_t$ follows a stationary AR(1) process.

$$g_t = \rho_g g_{t-1} + \sigma_g \epsilon^g_t$$

The transitory component $z_t$ also follows a stationary AR(1) process.

$$z_t = \rho_z z_{t-1} + \sigma_z \epsilon^z_t$$

The coefficients $\rho_g$ and $\rho_z$ are in $[0, 1)$, $\epsilon^g_t$ and $\epsilon^z_t$ are i.i.d. standard normal shocks.
Stochastic Information Friction

The economy features an imperfect information environment. Productivity is driven by two shocks: a permanent shock and a transitory shock. The agent does not observe the two shocks separately, but only the realized level of productivity. This creates a signal extraction problem for the agent. On top of observing the realized \( a_t \) each period, the agent receives an additional noisy signal regarding the permanent component of the productivity. This captures the idea that agents in the economy process public information, such as macro quantities reports, financial news, etc., and form exceptions regarding the economic fundamentals.

\[
s_t = x_t + \sigma_{st} \epsilon_t^s
\]  

This third source of information is also noisy. The signal \( s_t \) is driven by i.i.d. standard normal shocks \( \epsilon_t^s \), which I call "noise" shocks. The \( \sigma_{st} \) is time-varying. This captures the idea that the information environment of the economy is stochastic. I interpret this as **stochastic information friction**. The \( \sigma_{st} \) controls the degree of information imperfection. A high \( \sigma_{st} \) means severe information friction. I assume the logarithm of \( \sigma_{st} \) follows a stationary AR(1) process, and it is perturbed by i.i.d. standard normal shocks \( \eta_t^s \).

\[
\log(\sigma_{st}) = (1 - \kappa_s) \log(\bar{\sigma}_s) + \kappa_s \log(\sigma_{st-1}) + \omega_s \eta_t^s
\]  

This way of modeling the logarithm of \( \sigma_{st} \) ensures that the standard deviation of the shocks remains positive at all times. The \( \sigma_{st} \) is perturbed by i.i.d. innovations \( \eta_t^s \), which I call "Information Friction Shock" (IFS). A bad IFS increases \( \sigma_{st} \), and the information friction becomes more severe. The signal \( s_t \) becomes more noisy and less informative. It becomes more difficult for agents to extract the true economic fundamentals. As \( \sigma_{st} \to \infty \), \( s_t \) does not provide any additional information compared to the realizations of \( a_t \). As \( \sigma_{st} \to 0 \), households perfectly infer the permanent and transitory components to productivity; thus, the economy features a perfect information environment in that case.

Preference

The representative household has Epstein and Zin (1989) and Weil (1989) recursive preferences over streams of consumption \( C_t \) and leisure \( 1 - L_t \).

\[
V_t = \left\{ (1 - \beta) \left( C_t^\theta (1 - L_t)^{1-\theta} \right)^{1-\frac{1}{\gamma}} + \beta E_t \left[ V_{t+1}^{1-\gamma} \right]^{\frac{1-\frac{1}{\gamma}}{1-\frac{1}{\gamma}}} \right\}^{\frac{1}{1-\frac{1}{\gamma}}}
\]  

6
The preference parameters are the discount factor $\beta$, risk aversion $\gamma$, and the elasticity of intertemporal substitution (EIS) $\psi$. The parameter $\theta$ controls the leisure share. In this economy, the stochastic discount factor (SDF) can be written as:

$$M_{t+1} = \beta \left( \frac{C_{t+1}^{\theta}(1 - L_{t+1})^{1-\theta}}{C_t^{\theta}(1 - L_t)^{1-\theta}} \right)^{1-\frac{1}{\psi}} \left( \frac{C_{t+1}}{C_t} \right)^{-\frac{1}{\psi}} \left( \frac{V_{t+1}}{E_t \left[ V_{t+1}^{1-\gamma} \right]^{\frac{1}{\gamma}}} \right)^{\frac{1}{\psi} - \gamma}$$ (1.9)

The EZ framework features the timing preferences of the resolution of uncertainty. If $\gamma > 1/\psi$, the agent prefers an early resolution of uncertainty, and if $\gamma < 1/\psi$, a later resolution. When $\gamma = 1/\psi$, the representative agent is indifferent to the resolution of uncertainty, and the recursive preferences collapse to the CRRA case.

The representative household maximizes lifetime utility, subject to the resource constraint.

$$Y_t = C_t + I_t$$ (1.10)

Capital Market and Financial Friction

The household can convert consumption into capital by investing in capital markets. The firm accumulates capital according to the following inter-temporal law of motion:

$$K_{t+1} = (1 - \delta)K_t + \phi \left( \frac{I_t}{K_t} \right) K_t$$ (1.11)

Capital depreciates at the rate $\delta$. $\phi(\cdot)$ is a positive concave function, capturing capital market friction. I follow Jermann (1998) and specify the $\phi(\cdot)$ in a similar form.

$$\phi \left( \frac{I_t}{K_t} \right) = \tau_1 + \tau_2 \left( \frac{I_t}{K_t} \right)^{-\frac{1}{\xi_t}}$$ (1.12)

The $\tau_1$ and $\tau_2$ are constants. They are set to ensure that adjustment costs do not affect the steady state of the model. The only difference from Jermann (1998) is the time-varying $\xi_t$. The $\xi_t$ captures the elasticity of the investment-capital ratio with respect to Tobin’s Q. Higher $\xi_t$ represents smaller capital adjustment costs. If $\xi_t = +\infty$, the capital market becomes frictionless. The $\xi_t$ evolves according to the following equations:

$$\xi_t = (\xi - 1)e^{\xi_t} + 1$$ (1.13)

\[\text{1In particular, I set } \tau_1 = \left( e^{\mu + \delta - 1} - 1 \right) / (1 - \xi) \text{ and } \tau_2 = \left( e^{\mu + \delta - 1} \right)^{1/\xi} \]
\[ f_t = \rho f_{t-1} + \sigma f_t \epsilon_t \]  \hspace{1cm} (1.14)

Note the specification of (1.13) ensures the \( \xi_t \) is always greater than 1 if the steady state value \( \bar{\xi} \) is greater than 1. In a reduced form, \( f_t \) captures the financial friction in the market. It follows a stationary AR(1) process, and it is perturbed by i.i.d. standard normal shock \( \epsilon_t \). A positive \( \epsilon_t \) shock will increase the \( f_t \) and \( \xi_t \), and firms will pay less capital adjustment cost. In the model, I allow financial friction shock \( \epsilon_t \) and information friction shock \( \eta_t \) to be correlated, and use \( \rho^{sf} \) to denote the correlation coefficient between the two shocks. This is motivated by a vast body of literature that investigates the relationship between capital markets and information asymmetry (Greenwald et al. (1984) and Ivashina (2009)).

**Labor Market**

The representative household also supplies labor service \( L_t \) to the production firm. Wage rate \( w_t \) is set at the marginal product of labor. But the firm pays an extra wage adjustment cost as shown in the quadratic form below.

\[ \phi_t^L = \xi_w \left( 1 - \frac{A_{t-1} w_{t-1}}{A_{t-2} w_t} \right)^2 w_t L_t \]  \hspace{1cm} (1.15)

**Asset Prices**

The firm dividend \( D_t \) is specified as

\[ D_t = Y_t - \iota K_t - I_t - w_t L_t - \phi_t^L \]  \hspace{1cm} (1.16)

where \( \iota \) denotes operating cost per unit of capital. \( Y_t - \iota K_t \) represents the operating profit of the firm. The operating cost \( \iota K_t \) and wage adjustment cost \( \phi_t^L \) provide some operating leverage effects for the dividend claim. I assume these costs paid by the firm go to the household as a form of household income, so that the resource constraint in equation (1.10) still holds. The firm maximizes firm value, which is equal to the present discounted value of all current and future expected dividend flows. The firm’s equity return is

\[ R_t^E \equiv \frac{P_t + D_t}{P_{t-1}} \]  \hspace{1cm} (1.17)

where \( P_t \) denotes the price of a claim on all future dividends.
Equilibrium Conditions

The economy is non-stationary. To derive a stationary equilibrium, I de-trend all the non-stationary variables by $A_{t-1}$. A variable with a tilde represents its re-scaled counterpart. Note that the choice of $A_{t-1}$ as the normalization factor ensures the information consistency of the model, if $\bar{v}\bar{a}_t$ is in the agent’s information set at time $t-1$, so is the $\tilde{v}\tilde{a}_t$.

The welfare theorems hold in the model. The equilibrium can be characterized by the solution of the social planner’s problem. The value function is homogeneous of degree $\theta$. Taking advantage of this homotheticity property, the normalized stationary model is formulated in the recursive form as follows,

$$
\tilde{V}_t(x_t|t, g_t|t, z_t|t, \sigma_{st}, \tilde{K}_t) = \max_{\tilde{C}_t, L_t} \left\{ (1 - \beta) \left( \tilde{C}_t^{\theta} (1 - L_t)^{1-\theta} \right)^{\frac{1}{1-\psi}} + \tilde{A}_t^{\theta(1-\frac{1}{\psi})} \beta E_t \left[ \tilde{V}_{t+1}^{1-\gamma} \right]^{1-\frac{1}{1-\gamma}} \right\}
$$

subject to resource constraint. The variables $x_t|t$, $g_t|t$, and $z_t|t$ are the agent’s rational beliefs regarding each component of the productivity from Kalman learning. The optimal condition for consumption yields the Euler equation:

$$
1 = E_t [M_{t+1} R^f_{t+1}]
$$

The stochastic discount factor $M_{t+1}$ and investment return $R^f_{t+1}$ take the following form:

$$
M_{t+1} = \tilde{A}_t^{\theta(1-\frac{1}{\psi})-1} \beta \left( \tilde{C}_{t+1}^{\theta} (1 - L_{t+1})^{1-\theta} \right)^{\frac{1}{1-\psi}} \left( \tilde{C}_t^{\theta} (1 - L_t)^{1-\theta} \right)^{-1} \left( \frac{\tilde{V}_{t+1}}{E_t \left[ \tilde{V}_{t+1}^{1-\gamma} \right]^{1-\gamma}} \right)^{1-\gamma}
$$

The risk-free rate is just the reciprocal of expected SDF.

$$
R^f_t = \tau_2 \left( \frac{\tilde{I}_t}{\tilde{K}_t} \right)^{\frac{1}{1-\xi_t}} \left\{ \frac{\alpha \tilde{Y}_{t+1}}{\tilde{K}_{t+1}} + \frac{1}{\tau_2 \left( \frac{\tilde{I}_{t+1}}{\tilde{K}_{t+1}} \right)^{-\frac{1}{1-\xi_{t+1}}}} 1 - \delta + \tau_1 + \frac{\tau_2}{\xi_{t+1} - 1} \left( \frac{\tilde{I}_{t+1}}{\tilde{K}_{t+1}} \right)^{\frac{1}{1-\xi_{t+1}}} \right\}
$$

The optimal condition for labor choice satisfies the marginal rate of substitution between
consumption and leisure, equal to the marginal product of labor.

\[
\frac{1 - \theta}{\theta} \tilde{C}_t \left(1 - \frac{\theta}{1 - L_t}\right) = \frac{(1 - \alpha)\bar{Y}_t}{L_t}
\]  

(1.23)

1.3 Bayesian Learning and Kalman Filter

1.3.1 Derivation of Kalman Filter

In an environment in which agents have imperfect information regarding the true decomposition of the productivity shock into its permanent and transitory components, the rational agent forms expectations regarding the decomposition using the Kalman filter. This filter is a commonly used method to estimate the values of state variables of a dynamic system that is excited by stochastic disturbances and measurement noise. To formulate the signal extraction problem with the Kalman filter, I express the filtering problem in a general state space form, which consists of a transition equation (1.24) and a measurement equation (1.25).

\[
x_t = A_t x_{t-1} + B_t v_t \\
\mathbf{s}_t = C_t x_t + D_t w_t \\
v_t \sim \mathcal{N}(0, Q_t) \\
w_t \sim \mathcal{N}(0, R_t)
\]  

(1.24)  (1.25)

Uncertainty is captured by the first transition equation of the exogenous state vector \(x_t\). The agent observes the vector \(s_t\) expressed in the second measurement equation, which contains noise to the true signal. The \(A_t, B_t, C_t, D_t, Q_t\) and \(R_t\) are system matrices; \(v_t\) and \(w_t\) are vectors of mutually independent i.i.d. shocks. More specifically, for this model, the state vector is \(x_t = (x_t, g_t, z_t)^\top\), the measurement vector is \(s_t = (a_t, s_t)^\top\), the shock vectors are
\( v_t = w_t = (\epsilon^g_t, \epsilon^z_t, \epsilon^s_t) \), and the system matrices \( A_t, B_t, C_t, D_t, Q_t \) and \( R_t \) are

\[
A_t = \begin{bmatrix}
1 & \rho_g & 0 \\
0 & \rho_g & 0 \\
0 & 0 & \rho_z \\
\end{bmatrix},
\quad
B_t = \begin{bmatrix}
\sigma_g & 0 & 0 \\
\sigma_g & 0 & 0 \\
0 & \sigma_z & 0 \\
\end{bmatrix}
\]

\[
C_t = \begin{bmatrix}
1 & 0 & 1 \\
1 & 0 & 0 \\
\end{bmatrix},
\quad
D_t = \begin{bmatrix}
0 & 0 & 0 \\
0 & 0 & \sigma_{st} \\
\end{bmatrix}
\]

\[
Q_t = R_t = \begin{bmatrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1 \\
\end{bmatrix}
\]

Note that, in this setting, I express the standard deviation parameters of the shocks in the \( B_t \) and \( D_t \) matrices. \( Q_t \) and \( R_t \) are time-invariant \( 3 \times 3 \) identity matrices. In the baseline model, the parameters in matrix \( A_t \) and \( C_t \) are also time-invariant, so I simply drop the subscript \( t \), and use \( A, C, Q \) and \( R \) from now on. The time-varying matrix \( D_t \) contains the parameter \( \sigma_{st} \), which controls the degree of information friction in the economy. When \( \sigma_{st} = 0 \), \( s_t \) and \( a_t \) together fully reveal the components of productivity. This leads to an economy with a perfect information environment. The matrix \( B_t \) contains \( \sigma_g \) and \( \sigma_z \), which control the volatility of fundamental productivity. In this baseline model, fundamental uncertainty is constant, so I simply use \( B \) without the subscript \( t \). In the later section, I also consider an economy with fundamental stochastic volatility. In that case, matrices \( B_t \) and \( D_t \) are both time-varying.

To derive the recursive form of the Kalman filter, let me first define the following variables. I use \( x_{t|t} \) to denote the agent’s expectation regarding \( x_t \) based on all information at time \( t \), and \( P_{t|t} \) for the a posteriori error covariance matrix:

\[
x_{t|t} \equiv E_t[x_t]
\]

\[
P_{t|t} \equiv E_t[(x_t - x_{t|t})(x_t - x_{t|t})^T]
\]

Let \( x_{t|t-1} \) denote the agent’s expectation prior the new measurement \( s_t \), and \( P_{t|t-1} \) denote the a priori error covariance matrix:

\[
x_{t|t-1} \equiv E_{t-1}[x_t]
\]
\[ \mathbb{P}_{t|t-1} \equiv \mathbb{E}_t[(x_t - x_{t|t-1})(x_t - x_{t|t-1})^\top] \]

The essence of the Kalman filter algorithm is estimating the state process by implementing a linear form feedback control. The filter estimates the process state through transition equation, and then obtains feedback from the measurement equation. As such, the recursive form of the Kalman filter after the a posteriori error minimization problem falls into two groups: updating equations (1.26, 1.27, 1.28) and projecting equations (1.29, 1.30).

\begin{align*}
    x_{t|t} &= (I - K_tC)x_{t|t-1} + K_t s_t \\
    K_t &= \mathbb{P}_{t|t-1}C^\top (C\mathbb{P}_{t|t-1}C^\top + D_tD_t^\top)^{-1} \\
    \mathbb{P}_{t|t} &= (I - K_tC)\mathbb{P}_{t|t-1} \\
\end{align*}

The projecting equations are responsible for projecting forward the current state and error covariance estimate. They produce an a priori estimate for the next time step. The updating equations are responsible for the feedback. They incorporate the new measurement into the a priori estimate and produce an improved a posteriori estimate. The matrix \( K_t \) is the Kalman gain, a result from the estimate error minimization problem in each step. It controls the relative weights on the a priori estimate and new measurement.

\begin{align*}
    x_{t+1|t} &= Ax_{t|t} \\
    \mathbb{P}_{t+1|t} &= A\mathbb{P}_{t|t}A^\top + BQB^\top \\
\end{align*}

### 1.3.2 Time-Variant Bayesian Learning

With updating and projecting equations, I can express the Kalman filter problem in any recursive form. Particularly, in the form of a priori error covariance matrix, I derive the algebraic Riccati equation:

\[ \mathbb{P}_{t+1|t} = A(I - K_tC)\mathbb{P}_{t|t-1}A^\top + BQB^\top \]

When system matrices are all time-invariant, Kalman gain, a priori and a posteriori error covariance matrices converge monotonically to a time-invariant solution. I can get these steady state values by recursively solving the Riccati equation. Using \( \hat{\mathbb{P}}_t \) and \( \tilde{\mathbb{P}}_t \) to denote the steady a priori and a posteriori error covariance matrix, the recursive Riccati algorithm
is expressed in the following three equations.

\[
\hat{P} = A(\mathbb{I} - KC)\hat{P}A^\top + BQB^\top \tag{1.32}
\]

\[
K = \hat{P}C^\top (C\hat{P}C^\top + DRD^\top)^{-1} \tag{1.33}
\]

\[
\hat{P} = (\mathbb{I} - KC)\hat{P} \tag{1.34}
\]

However, in my model, the learning problem is time-variant. The matrix \(D_t\) is time-varying because of the \(\sigma_{st}\). Thus, the Kalman learning variables \(K_t, \hat{P}_t\) and \(\hat{P}_t\) are all time-varying, and depend on the state of \(\sigma_{st}\) at time \(t\). I assume \(\sigma_{st}\) is public information to agent at time \(t\). Unfortunately, there are no close form solutions for the \(K_t/\hat{P}_t/\hat{P}_t\)-to-\(\sigma_{st}\) mapping. I use a numerical method to approximate these mappings. First, I select a reasonably wide range of \(\sigma_s\) space \([\sigma_{sLB}, \sigma_{sUB}]\), and discretize it with \(n_s\) points. Then, for each \(\sigma_{si}^s, \ i = 1, 2, \ldots n_s\), I recursively solve the Riccati equation, and get the corresponding Kalman gain \(K^i\), similarly for the a priori and a posteriori error covariance matrix \(\hat{P}^i\) and \(\hat{P}^i\). Finally, I use an \(n_p\) order of Chebyshev polynomials or power polynomials to approximate these \(n_s\) pair mappings with a reasonably low approximation error level. Generally, an \(n_p = 5\) order approximation for \(n_s = 100\) pair mapping is good enough to maintain the approximation error below \(1 \times 10^{-4}\) level.

### 1.3.3 Dynamics of Bayesian Beliefs

To formulate the representative agent’s optimization problem in the recursive form and solve the model, I need to solve the law of motion of the agent’s a posteriori beliefs \(x_{t|t}\) regarding fundamental productivity. In other words, \(x_{t|t}\) are state variables. The fundamental productivity variables, \(x_t, g_t\) or \(z_t\) are not state variables, since they are unobservable. To derive the dynamics of \(x_{t|t}\), I re-write the following two equations:

\[
\begin{align*}
x_{t|t} &= Ax_{t-1|t-1} + K_t (s_t - CAx_{t-1|t-1}) \tag{1.35} \\
s_t &= CAx_{t-1|t-1} + (s_t - CAx_{t-1|t-1}) \tag{1.36}
\end{align*}
\]

The first equation comes from (1.26) and (1.29); the second equation is a mathematical identity. Let me define \(u_t = s_t - CAx_{t-1|t-1}\). This term represents the measurement surprise, because \(CAx_{t-1|t-1}\) is the best estimate of time \(t\) signal, \(s_{t|t-1}\), based on all available information at \(t-1\). Let me also define \(\Sigma_t = Var_{t-1}[u_t]\). I derive the relationship of \(\Sigma_t\) and...
system matrices in equation (1.37).

\[ \Sigma_t = C \left( A P_{t-1|t-1} A^T + B Q B^T \right) C^T + D_t R D_t^T \]  

\hspace{1cm} (1.37)

Then I decompose the matrix \( \Sigma_t \) as

\[ \Sigma_t = H_t H_t^T \]  

\hspace{1cm} (1.38)

and re-write the joint dynamics of \( x_{t|t} \) and \( s_t \) in the following form:

\[ x_{t|t} = A x_{t-1|t-1} + K_t H_t \hat{u}_t \]  

\hspace{1cm} (1.39)

\[ s_t = C A x_{t-1|t-1} + H_t \hat{u}_t \]  

\hspace{1cm} (1.40)

where \( \hat{u}_t \) is a vector of mutually independent i.i.d. standard normal shocks. Equations (1.39) and (1.40) fully characterize the evolution of the agent’s beliefs. With these two equations, I convert the original model with unobservable information to an equivalent model with full information and correlated shocks.

1.4 Quantitative Analysis

The goal of this section is to evaluate the quantitative effects of stochastic information friction. To do so, I numerically solve the DSGE model with the 3rd-order perturbation method. A real business cycle model with information friction shocks can simultaneously match the key moments of macroeconomic variables and asset returns. The macroeconomic effects are captured by the impulse responses to the shocks. Though simulation, I also show that information friction shocks are important for capturing the dynamics of real business cycle quantities.

1.4.1 Numerical Method

The body of literature on DSGE computation methods is very large. Commonly used methods include value function iteration, perturbation, Chebychev polynomials, finite element methods, etc. Here I select the perturbation method that I find most promising in terms of accuracy and efficiency and implement a 3rd-order perturbation of the model. The 1st-order perturbation is useless here, particularly because of the recursive preference and second moment shocks ingredients in the model. Note that the most common solution methods, linearization and log-linearization, are particular cases of 1st-order perturbation. Essentially,
the decision rules from 1st-order approximation are certainty equivalent. Therefore, they
depend on $\psi$, but not on $\gamma$ or $\sigma_{st}$. In order to allow recursive preference and second moment
shocks to play a role, I need to go at least to 2nd-order perturbation to have terms that
depend on $\gamma$ or $\sigma_{st}$. Even in 2nd-order approximation, the effect of uncertainty shocks is
limited. I say limited because the mean is affected but not the dynamics. For this reason,
we are interested especially in the time-varying risk premia; a 3rd-order or even higher order
perturbation is preferred. I solve the model using a 3rd-order perturbation method with
Dynare and MatLab. For a 4th-order approximation, I use Mathematica, which works very
well with symbolic algebra and symbolic equation manipulations. I perform the higher order
perturbation to mitigate the concerns that lower order approximation may contain large
errors if the model exhibits high non-linearity. The accuracy of 3rd-order perturbation in
terms of Euler equation errors is excellent – even far way from the steady state. Throughout
the paper, I report the numerical results from the 3rd-order perturbation solutions.

1.4.2 Parameterization

I select a benchmark calibration for the numerical computations. The parameter values are
chosen to match basic observations of the US economy, and they align closely with common
choices in the literature. Table 1.1 summarizes the full set of parameters in my benchmark
calibration. I take one period in the model to represent one quarter.

On the preference side, the quarterly discount factor $\beta$ is set to 0.994 to match the risk-
free interest rate. The value for labor share $\theta$ is set to 0.36, implying that the share of time
devoted to work is one-third in the steady state. Aligned with the long-run risk literature,
the relative risk aversion and EIS are set as $\gamma = 8$ and $\psi = 2$.

On the production side, the long run deterministic growth rate $\mu$ is set to 0.0049 to match
the GDP growth in the US. The capital exponent in production function $\alpha$ is calibrated
to match the capital income share. The capital depreciation rate is set as 2.5%, which is
standard for a quarterly frequency model. The steady state value of capital adjustment cost
$\xi$ is set to 20.

On the information friction side, the average information friction level is set as $\bar{\sigma}_s = 0.0147$,
which is consistent with Blanchard et al. (2013). The persistence of information friction shock
$\bar{\kappa}_s$ is set to 0.9, and the standard deviation of information friction shock $\omega_s$ is set to 0.02.

There is no debt in the model. In data, equity returns are levered, and some portion of
dividend growth volatility is due to idiosyncratic payout shocks. To better compare the data
with the model, I multiply risk premia and standard deviations of stock returns by a leverage
parameter of 2.
Table 1.1: Parameterization - Baseline Model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preference</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discount factor</td>
<td>$\beta$</td>
<td>0.994</td>
</tr>
<tr>
<td>Risk aversion</td>
<td>$\gamma$</td>
<td>8.0</td>
</tr>
<tr>
<td>Elasticity of intertemporal substitution</td>
<td>$\psi$</td>
<td>2.0</td>
</tr>
<tr>
<td>Leisure exponent in utility</td>
<td>$\theta$</td>
<td>0.36</td>
</tr>
<tr>
<td><strong>Technology</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital exponent in production</td>
<td>$\alpha$</td>
<td>0.34</td>
</tr>
<tr>
<td>Depreciation rate</td>
<td>$\delta$</td>
<td>0.025</td>
</tr>
<tr>
<td>Deterministic growth rate</td>
<td>$\mu$</td>
<td>0.0049</td>
</tr>
<tr>
<td>Persistence of permanent productivity shock</td>
<td>$\rho_g$</td>
<td>0.89</td>
</tr>
<tr>
<td>Volatility of permanent productivity shock</td>
<td>$\sigma_g$</td>
<td>0.002</td>
</tr>
<tr>
<td>Persistence of transitory productivity shock</td>
<td>$\rho_z$</td>
<td>0.89</td>
</tr>
<tr>
<td>Volatility of transitory productivity shock</td>
<td>$\sigma_z$</td>
<td>0.015</td>
</tr>
<tr>
<td>Capital adjustment cost</td>
<td>$\xi$</td>
<td>20.0</td>
</tr>
<tr>
<td>Persistence of financial friction shock</td>
<td>$\rho_f$</td>
<td>0.80</td>
</tr>
<tr>
<td>Volatility of financial friction shock</td>
<td>$\sigma_f$</td>
<td>0.04</td>
</tr>
<tr>
<td>Operating cost</td>
<td>$\iota$</td>
<td>0.0018</td>
</tr>
<tr>
<td>Wage adjustment cost</td>
<td>$\xi_w$</td>
<td>15.0</td>
</tr>
<tr>
<td><strong>Information Friction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average level of information friction</td>
<td>$\bar{\sigma}_s$</td>
<td>0.0147</td>
</tr>
<tr>
<td>Persistence of information friction shock</td>
<td>$\kappa_s$</td>
<td>0.90</td>
</tr>
<tr>
<td>Volatility of information friction shock</td>
<td>$\omega_s$</td>
<td>0.02</td>
</tr>
<tr>
<td><strong>Correlation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Corr($\eta_{it}^s$, $\epsilon_{it}^f$)</td>
<td>$\varrho_{sf}$</td>
<td>-0.90</td>
</tr>
</tbody>
</table>

1.4.3 Impulse Responses

Figure 1.1 shows the impulse responses for four observed macro variables to one standard deviation of permanent technology shock, transitory technology shock, and noise shock respectively. All four variables show similar patterns in response to the three shocks. They respond primarily to the transitory productivity shock and noise shock in the short run. In response to a permanent shock, they build up slowly over time, because it takes a longer period for agents to recognize the permanent shocks. Noise shock generates some short-term fluctuations, but the response also dies down very fast. In response to a noise shock, agents consume more and invest less, because they assign a positive probability to the case that the shock might be a permanent productivity shock. Agents quickly learn that the shock is just
By nature, the information friction shocks are second moment shocks. They affect the shape of impulse responses by affecting the initial state when other shocks hit the economy. In Figures 1.2, 1.3 and 1.4, I plot the impulse responses to three shocks in two different scenarios, in which the initial state is high ($\sigma_{st} = H$) or low ($\sigma_{st} = L$) information friction. I also plot the impulse responses for the perfect information case. This perfect information scenario is a special case where agents fully observe the permanent and transitory components; it is
captured as $\sigma_{st} = 0$.

Figure 1.2: Impulse Responses to Permanent Productivity Shock

With perfect information, in response to a permanent productivity shock, agents consume more, cut investments, and work less, because they know productivity will be high tomorrow. However, when there is information friction, agents assign a positive probability to the case that the shock might just be noise or transitory. The more severe information friction is, the less probability agents assign to a permanent shock. So agents consume less, invest more, and work harder when information friction is severe, as shown in Figure 1.2. Agents display consumption smoothing behavior.

In response to a transitory productivity shock, the magnitude of initial response is very similar under the three scenarios shown in Figure 1.3. However, the degree of information friction does affect persistence. When $\sigma_{st}$ is high, responses to transitory shocks die out very fast, because productivity shocks are less informative when information friction is high. Thus, the transitory productivity shocks are more likely to be treated as noises.

With perfect information, agents do not respond to any noise shocks. With an imperfect information environment, noise shocks generate short-term fluctuations. With Bayesian
learning, agents quickly recognize the disturbance is just noise, so responses die out very fast. When $\sigma_{st}$ is high, responses to noise shock are more persistent, and die out slowly.

1.4.4 Business Cycle Moments

I report the model-implied moments of macroeconomic quantities and asset prices from the baseline model in Table 1.2. The moments in actual data are estimated using quarterly US time series data of GDP, consumption, investment and employment from the period 1948:I to 2014:IV. Further details of variables’ definition and construction may be found in the Appendix. The model matches the key moments of the US data closely. For the simulated data, the table shows the mean values across simulations, along with the 5th and 95th percentile values in brackets.

For most of the moments of interest, the range of empirical estimates falls inside the 90 percent confidence intervals generated by the model. The volatility of output growth is 1.53%, compared with 1.38% in the data. But the volatility of investment growth and
consumption growth in the model are a little bit off their empirical counterpart. The ratio of consumption growth volatility to output growth volatility is 0.61, and the ratio of investment growth volatility to output growth volatility is 3.40. The implied levered equity premium of the model is 4.23%, matching the historical mean of the CRSP stock market log excess returns.

1.5 Asset Pricing Implication

The goal of this section is to explore asset pricing implications from the model. To do so, I first derive the price of information friction shock from the model solutions. IFS carries a negative price of risk. Then I investigate the mechanism of generating a negative price of risk by showing the impulse responses to the information friction shocks.
Table 1.2: Business Cycle Moments - Baseline Model

<table>
<thead>
<tr>
<th>Macroeconomic Quantities</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma[\Delta y]$</td>
<td>1.38%</td>
<td>1.53%</td>
</tr>
<tr>
<td></td>
<td>[1.41% 1.67%]</td>
<td></td>
</tr>
<tr>
<td>$\sigma[\Delta c]/\sigma[\Delta y]$</td>
<td>0.37</td>
<td>0.61</td>
</tr>
<tr>
<td>$\sigma[\Delta i]/\sigma[\Delta y]$</td>
<td>3.45</td>
<td>3.40</td>
</tr>
<tr>
<td>$\sigma[\Delta l]/\sigma[\Delta y]$</td>
<td>0.37</td>
<td>0.67</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Asset Prices</th>
<th>Data</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E[r_t - r^f_t]$</td>
<td>4.09%</td>
<td>4.23%</td>
</tr>
<tr>
<td></td>
<td>[3.65% 4.83%]</td>
<td></td>
</tr>
<tr>
<td>$\sigma[r_t - r^f_t]$</td>
<td>15.80%</td>
<td>18.50%</td>
</tr>
<tr>
<td></td>
<td>[16.74% 20.10%]</td>
<td></td>
</tr>
</tbody>
</table>

Note – The table compares moments of the data to simulated moments from the baseline model. I consider log output growth variability, relative variance of consumption to output, relative variance of investment to output, relative variance of labor to output, equity premium, and equity excess return volatility. Moments of actual data are estimated using quarterly US time series data of GDP, consumption, investment and employment from 1948:I to 2014:IV. Moments of simulated data from the model are at quarterly frequency. I report mean moments, along with the 5th and 95th percentiles across 1,000 simulations, each with a length of 50 years.

1.5.1 Price of Risk

The innovations to the stochastic discount factor are important as they characterize the risks that affect investors’ marginal utility and determine risk compensation. To pin down the price of information friction shock risk, I express the innovations to the log of stochastic discount factor $m_t \equiv \log(M_t)$ from the model solutions.

$$m_t - E_{t-1}[m_t] = -\lambda_t^g \hat{g}_t - \lambda_t^z \hat{z}_t - \lambda_t^f \hat{f}_t - \lambda_t^s \eta_t^s$$  \hspace{1cm} (1.41)

Since I am interested in the price of risk associated with information friction, I focus on the $\lambda_t^s$ part. I solve the model with 3rd-order perturbation; therefore, the price of risk is time-variant, and $\lambda_t^s$ includes the 2nd-order cross terms among all the state variables and
exogenous shocks in the model. Here I consider the unconditional mean of the $\lambda_t^s$. In such a way, all the interaction terms are eliminated, leaving only a constant term.

$$\bar{\lambda}^s \equiv E[\lambda_t^s] = -0.0032 \quad (1.42)$$

Note that this approach is essentially the same as solving the model with 1st-order perturbation, or the log-linearization technique. The price of information friction risk is negative. A positive shock to the information friction induces the marginal utility of consumption to increase, i.e. in a bad state of world. On average, the price of risk for one standard deviation\(^2\) shock to the information friction is 0.32%.

1.5.2 Mechanism Inspection

Figure 1.5 shows the impulse responses for six observed macro variables, as well as the kernel and dividend, to one standard deviation of information friction shock. In response to a positive shock to information friction, agents consume less, invest more, and work more hours. As a result, capital and output increase and dividend drops significantly. However, agents’ marginal utility increases in response to a positive information friction shock. Dividend and SDF move in opposite directions. This means dividend payments are low when agents are in a bad state of world. Thus, dividend claim carries a positive risk premium associated with information friction shock.

Financial friction also amplifies this co-movement effect. Information friction shocks and financial friction shocks are negatively correlated in the model. A positive information friction shock also decreases the $\xi_t$, as shown in Figure 1.5. Note, the lower $\xi_t$ represents higher capital adjustment costs. The friction in capital markets becomes more severe when information friction is high. On average, dividend drops more when capital market friction is higher. In Figure 1.6, I plot the impulse responses of SDF and dividend to the information friction shock, under two scenarios. Dividend is more volatile when the correlation between information friction and financial market friction is higher. There is vast evidence in the literature that investigating the relationship between capital markets and imperfect information showing external financing is more expensive with the existence of asymmetrical information. To sum up, the interaction between information friction and financial market friction amplifies the effect of information uncertainty on asset valuations.

\(^2\)All the shocks in the model are standardized normal shocks with unit variance.
1.6 Empirical Evidence

In this section, I test the model’s asset pricing implication empirically. To do so, I construct a proxy for information friction shock using Survey of Professional Forecasters (SPF) data and measure of macroeconomic uncertainty from Jurado et al. (2015). Specifically, I first construct the measure of belief dispersion from the SPF data; then, I orthogonalize the time series of belief dispersion using estimates from Jurado et al. (2015) to control any effects from the fundamental uncertainty channel. The remaining part is driven by the information uncertainty channel; I attribute it as the proxy for information friction shock. With this empirical proxy for information friction shock, I use Fama-French 25 size-value portfolios to test whether IFS is a priced risk factor. The results show a significant negative price of risk for these test assets. I also explore the cross-sectional return predictability using portfolio sorts methodology. My main finding is that firms with high exposure to information friction shock tend to have lower returns, on average, than firms with low information friction shock exposure. This finding is consistent with the model prediction of negative price of information friction risk.

1.6.1 Measure of Information Friction Shocks

The main interest of this paper is to study the uncertainty effect from the information friction channel. In the set up of my model, time-varying information friction directly affects agents’ a posteriori estimate variance. When the information friction becomes more severe, agents are more unsure about true fundamental productivity and the variance of their beliefs become wider. Thus, I first construct the measure of belief dispersion using the Survey of Professional Forecasters data.

The Federal Reserve Bank of Philadelphia provides extensive panel data on economic variable forecasts by professional economists. Each economist is asked to forecast a large set of macroeconomic and financial variables over the current quarter and the subsequent four quarters. To ensure panelists have the same information set, the Philadelphia Fed synchronizes the survey timing with the release of Bureau of Economic Analysis’ advance report, which contains the first estimate of GDP from the previous quarter. After this report is released to the public, the Philadelphia Fed sends out survey questionnaires with all recent data from the advance report. Usually, the deadline for survey responses is set one or two weeks before the second month of each quarter, and the Philadelphia Fed releases the survey results at the end of second month of each quarter. Figure 1.7 shows the timing of the Survey of Professional Forecasters.

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Although SPF provides forecasts over different horizons, I focus on the forecasts over the current quarter, not any future quarters. The reason is imperfect information prevents the agents from observing the true current state, not future states. The forecasts of future states are more likely to be driven by the fundamental uncertainty, not imperfect information. As shown in Figure 1.7, when economists are asked to forecast the current quarter GDP, they are almost at the end of the second month of the current quarter. Therefore, a significant portion of the individual-level forecast dispersion is due to information friction. To some extent, this helps me control some fundamental uncertainty effects. SPF also provides forecasts of many macroeconomic and financial variables. However, I focus on the nominal GDP because this directly relates to the productivity in my model set up. As a result, the belief dispersion series is constructed using the individual-level forecast of nominal GDP of the current quarter from the SPF data. I define the belief dispersion \((BD)\) as the difference between the 75 and 25 percentiles of logarithm of nominal GDP across all individual forecasts for each quarter. For robustness check, I also consider the 80-20 and 90-10 dispersion measures. The results do not change much.

\[
BD_t = \text{Pctile}(\log(NGDP_{it}), 75) - \text{Pctile}(\log(NGDP_{it}), 25)
\]  

The cross-sectional forecasts dispersion is used in other studies as a proxy for macroeconomic uncertainty, e.g. Bloom (2009), Bachmann et al. (2013) and Bali et al. (2014). In the model, belief dispersion is driven by two channels: the information channel, and the fundamental uncertainty channel. To get a clean proxy for information friction shocks, I orthogonalize the measure of belief dispersion with a macro uncertainty proxy from Jurado et al. (2015). Jurado et al. (2015) exploit a very rich data environment and provide direct estimates of macroeconomic uncertainty \((MU)\). I use two methods in this orthogonalization practice. The first method is simply regressing belief dispersion \((BD)\) over macro uncertainty \((MU)\). The information friction shocks \((IFS)\) are defined as the residuals of this OLS regression.

\[
BD_t = \beta MU_t + IFS_t
\]

The second method involves two steps. In the first step, I get the unexpected change of belief dispersion \((BDS)\), and unexpected change of macro uncertainty \((MUS)\), by fitting a AR(1) regression of the \(BD\) and \(MU\) series. Then, in the second step, I regress \(MUS\) over
\( BDS; \) the residuals are defined as information friction shocks (\( IFS \)).

\[
\begin{align*}
BD_t &= \rho BD_{t-1} + BDS_t \\
MU_t &= \rho MU_{t-1} + MUS_t \\
MUS_t &= \rho BDS_t + IFS_t
\end{align*}
\] (1.45)

The empirical results are not sensitive to the choice of these two methods. I report the result with the second orthogonalization method. Note that all the residuals from OLS regressions are standardized, so that \( BDS, MUS \) and \( IFS \) all have unit variance.

1.6.2 Risk Pricing

The model implies a negative price of information friction risk. I evaluate the performance of the baseline model using 25 Fama-French size and book-to-market portfolios as test assets. I follow the two-pass regression procedure in Boguth and Kuehn (2013). First, for each test asset, I obtain unconditional risk loadings from a time-series regression of excess returns on information friction shock (\( IFS \)) and other factors, depending on the model specification. In the second pass, I estimate the prices of risk by cross-sectionally regressing average excess returns on the first-pass loadings. The results from the second-pass regression are reported in Table 1.3. I consider several specifications. The results confirm that \( IFS \) is a negatively priced factor. The Fama-French 3 factors specification explains the test asset returns with an \( R^2 \) of 69%. Adding the \( IFS \) factor into the Fama-French 3 factors specification improves the explanatory power with an \( R^2 \) of 78%. The last full model specification, including the \( IFS \) factor, Fama-French 3 factors and momentum factor, achieves an \( R^2 \) of 82%.

1.6.3 Portfolio Sort

I obtain risk loadings as slope coefficients from time-series regressions of individual stock returns on information friction shocks, controlling the Fama-French 3 factors and the momentum factor. In particular, for each security, I estimate factor loadings in each quarter using the previous 5 years of quarterly observations.

\[
r^i_t - r^f_t = \alpha^i_t + \beta^i_t IFS_t + \gamma^i_t Control_t + \varepsilon^i_t
\] (1.48)

With the estimates of each stock’s risk loadings, I am able to test whether future returns are predicted by the exposure to innovations in information friction, using the portfolio
Table 1.3: IFS Pricing with Fama-French 25 Size-Value Test Portfolios

<table>
<thead>
<tr>
<th></th>
<th>IFS</th>
<th>MKT</th>
<th>SMB</th>
<th>HML</th>
<th>UMD</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model I</td>
<td>-0.344</td>
<td>0.000</td>
<td>0.012</td>
<td>0.012</td>
<td>0.026</td>
<td>9.27</td>
</tr>
<tr>
<td></td>
<td>(1.53)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model II</td>
<td>-0.019</td>
<td>0.004</td>
<td>0.012</td>
<td>0.012</td>
<td>0.026</td>
<td>69.13</td>
</tr>
<tr>
<td></td>
<td>(-1.38)</td>
<td>(2.65)</td>
<td>(6.25)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model III</td>
<td>-1.490</td>
<td>0.005</td>
<td>0.006</td>
<td>0.011</td>
<td>0.020</td>
<td>81.25</td>
</tr>
<tr>
<td></td>
<td>(-3.56)</td>
<td>(-0.47)</td>
<td>(4.56)</td>
<td>(7.11)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model IV</td>
<td>-0.006</td>
<td>0.004</td>
<td>0.012</td>
<td>0.026</td>
<td>0.020</td>
<td>71.38</td>
</tr>
<tr>
<td></td>
<td>(-0.34)</td>
<td>(2.60)</td>
<td>(6.40)</td>
<td>(1.17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model V</td>
<td>-1.447</td>
<td>0.001</td>
<td>0.006</td>
<td>0.011</td>
<td>0.020</td>
<td>81.62</td>
</tr>
<tr>
<td></td>
<td>(-3.36)</td>
<td>(-0.04)</td>
<td>(4.31)</td>
<td>(7.02)</td>
<td>(1.07)</td>
<td></td>
</tr>
</tbody>
</table>

Note – The table reports market prices of risk from quarterly cross-sectional regressions of average excess returns on estimated factor loadings, using Fama-French 25 size-value portfolios. The factors are information friction shock (IFS), Fama-French 3 factors (MKT, SMB, HML), and momentum factor (UMD). For each model, I report the estimated prices of risk, and the $R^2$. The t-statistics are reported in parentheses.

sort methodology. To make an accurate estimate of the price of dispersion shock, I need assets with substantial dispersion in their exposure to the dispersion shock. Thus, I create portfolios of firms sorted on their past sensitivity to the dispersion shock, and focus on the spread between highest and lowest decile portfolios. At the end of each quarter, I sort all stocks into portfolios based on their estimated risk loadings from the time-series regression (1.48). Portfolios are held for three months and re-balanced every quarter.

Table 1.4 shows the average excess returns and risk characteristics for the 10 portfolios of stocks sorted on their past sensitivity to the information friction shock. First, these portfolios display a declining pattern of average excess returns, ranging from 85 bps to 46 bps per month. Second, the volatility of these portfolios displays a U-shape from low decile to high decile. The volatility in the middle is around 4.6 percent per month, where the volatility of low and high portfolios is above 7.7 percent per month.
Figure 1.5: Impulse Responses to Information Friction Shock

- Output
- Consumption
- Investment
- Labor
- Capital
- Capital Market Friction $-\xi$
- SDF
- Dividend
Figure 1.6: Impulse Response of SDF and Dividend to Information Friction Shock

![Impulse Response Graph]

Figure 1.7: Timing of the Survey

*Release of BEA advance report of the NIPA (Estimate of GDP for previous quarter)*

*Deadline for survey responses*

*Release of survey results*
Table 1.4: Cross-Setional Return Predictability

<table>
<thead>
<tr>
<th></th>
<th>Low</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>High</th>
<th>High - Low</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess Return $E[r_t - r_f]$</td>
<td>0.85</td>
<td>0.63</td>
<td>0.53</td>
<td>0.66</td>
<td>0.65</td>
<td>0.63</td>
<td>0.50</td>
<td>0.52</td>
<td>0.61</td>
<td>0.46</td>
<td>-0.39</td>
</tr>
<tr>
<td>Volatility $\sigma[r_t - r_f]$</td>
<td>7.64</td>
<td>6.15</td>
<td>4.93</td>
<td>4.84</td>
<td>4.63</td>
<td>4.54</td>
<td>4.97</td>
<td>5.48</td>
<td>6.14</td>
<td>7.86</td>
<td>4.74</td>
</tr>
<tr>
<td>Sharpe Ratio</td>
<td>0.11</td>
<td>0.10</td>
<td>0.11</td>
<td>0.14</td>
<td>0.14</td>
<td>0.14</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.06</td>
<td>-0.08</td>
</tr>
<tr>
<td>Average $\beta^{IFS}$</td>
<td>-0.182</td>
<td>-0.083</td>
<td>-0.050</td>
<td>-0.026</td>
<td>-0.007</td>
<td>0.011</td>
<td>0.031</td>
<td>0.055</td>
<td>0.092</td>
<td>0.218</td>
<td>0.401</td>
</tr>
<tr>
<td>$\alpha$ - CAPM</td>
<td>0.08</td>
<td>-0.02</td>
<td>-0.01</td>
<td>0.14</td>
<td>0.14</td>
<td>0.13</td>
<td>-0.06</td>
<td>-0.08</td>
<td>-0.04</td>
<td>-0.34</td>
<td>-0.42</td>
</tr>
<tr>
<td></td>
<td>(0.43)</td>
<td>(-0.16)</td>
<td>(-0.09)</td>
<td>(1.47)</td>
<td>(1.89)</td>
<td>(1.70)</td>
<td>(-0.77)</td>
<td>(-0.89)</td>
<td>(-0.34)</td>
<td>(-1.82)</td>
<td>(-1.98)</td>
</tr>
<tr>
<td>$\alpha$ - FF3</td>
<td>0.23</td>
<td>0.06</td>
<td>0.07</td>
<td>0.19</td>
<td>0.15</td>
<td>0.16</td>
<td>-0.03</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.32</td>
<td>-0.55</td>
</tr>
<tr>
<td></td>
<td>(1.40)</td>
<td>(0.51)</td>
<td>(0.78)</td>
<td>(1.99)</td>
<td>(1.89)</td>
<td>(2.11)</td>
<td>(-0.37)</td>
<td>(-0.70)</td>
<td>(-0.60)</td>
<td>(-2.18)</td>
<td>(-2.46)</td>
</tr>
<tr>
<td>$\alpha$ - FF3+UMD</td>
<td>0.30</td>
<td>0.14</td>
<td>0.03</td>
<td>0.29</td>
<td>0.15</td>
<td>0.13</td>
<td>-0.02</td>
<td>-0.06</td>
<td>-0.03</td>
<td>-0.28</td>
<td>-0.58</td>
</tr>
<tr>
<td></td>
<td>(1.61)</td>
<td>(1.03)</td>
<td>(0.34)</td>
<td>(3.12)</td>
<td>(1.90)</td>
<td>(1.68)</td>
<td>(-0.32)</td>
<td>(-0.57)</td>
<td>(-0.27)</td>
<td>(-1.87)</td>
<td>(-2.29)</td>
</tr>
</tbody>
</table>

Note – The table reports summary statistics for 10 value-weighted portfolios sorted on IFS exposure. I report mean excess returns over the risk-free rate, excess return volatility, Sharpe ratio, and average IFS beta in each portfolio. I also report the abnormal returns for each portfolio. Monthly portfolio abnormal returns are computed by running time series regressions of portfolio excess returns on risk factors. The t-statistics are reported in parentheses. The sample includes monthly data from October 1973 to December 2013.
In the last column, I also report the excess returns of a long-short strategy that invests in the high exposure portfolio and sells the low exposure portfolio. The average monthly returns of this zero investment portfolio is -0.39%, yielding an annual return of around -5%. Cross-sectional differences in returns might not be surprising if the IFS betas covary with other variables known to predict returns. To mitigate this concern, I regress the portfolio returns on the most commonly used factors, such as Fama-French 3 factors and the momentum factor. The α and its t-statistic are also reported in Table 1.4. The long-short portfolio earns a significant -55 bps excess return per month, or about -6.8% per annum.

1.7 Information Uncertainty and Fundamental Uncertainty

So far, I have shown the importance of stochastic information friction for capturing the dynamics of real business cycle quantities and asset prices. The main mechanism is time-varying information friction affecting agents’ a posteriori estimate variance. When information friction becomes more severe, the agent is more unsure about the true fundamental productivity, belief dispersion becomes wider, uncertainty becomes larger. Importantly, this time-variant uncertainty feature is solely generated from the information channel; it is not related to fundamental productivity uncertainty. In the baseline model, productivity uncertainty is constant. In this section, I allow the fundamental productivity uncertainty to be time-varying. As a result, time-variant uncertainty is generated from two channels.

Since the seminal work of Bloom (2009), a large and growing body of literature has studied the effect of uncertainty shock in explaining macroeconomic dynamics. In this literature, the information environment is usually perfect; agents know the fundamentals today, but are not sure about the volatility of productivity tomorrow due to uncertainty shock. This clearly differentiates from the information uncertainty channel. Information uncertainty from the baseline model refers to agents’ belief uncertainty regarding the fundamentals today. To better understand the time-varying uncertainty from these two channels, I build a DSGE model with both information friction shocks and uncertainty shocks in next section.

1.7.1 Extended Model with Uncertainty Shock

As in my baseline model, the productivity $a_t$ follows the process (1.3) with component $x_t$ and transitory component $z_t$. Permanent growth $g_t \equiv \Delta x_t$ follows the same AR(1) process in (1.4).

$$ a_t = x_t + z_t $$  \hspace{1cm} (1.49)
\[ g_t = \rho g_{t-1} + \sigma g \epsilon^g_t \]  

(1.50)

The transitory productivity \( z_t \) follows a similar AR(1) process in (1.5), but with time-varying \( \sigma_{zt} \) to incorporate the uncertainty shocks. Fundamental uncertainty level is perturbed by i.i.d. standard normal shocks \( \eta^z_t \), with variance \( \omega^2_z \).

\[ z_t = \rho_z z_{t-1} + \sigma z_t \epsilon^z_t \]  

(1.51)

\[ \log(\sigma_{zt}) = (1 - \kappa_a) \log(\bar{\sigma}_z) + \kappa_a \log(\sigma_{zt-1}) + \omega_z \eta^z_t \]  

(1.52)

The information environment is still imperfect, and features time-varying frictions. As in my baseline model, the agent observes \( a_t \) and an additional signal \( s_t \), but is imperfectly informed about the true decomposition of \( x_t \) and \( z_t \).

\[ s_t = x_t + \sigma_{st} \epsilon^s_t \]  

(1.53)

\[ \log(\sigma_{st}) = (1 - \kappa_s) \log(\bar{\sigma}_s) + \kappa_s \log(\sigma_{st-1}) + \omega_s \eta^s_t \]  

(1.54)

All the other setups are the same as the baseline model.

1.7.2 Quantitative Analysis

In this extended model, with both information friction shock and uncertainty shock, the agent’s beliefs dispersion is time-varying and is affected by both shocks simultaneously. To better understand this, I take a look at modified equations (1.37), (1.38) and (1.39) in agents’ Bayesian learning problem.

\[
\begin{align*}
\Sigma_t &= C (A P_{t-1|t-1} A^T + B_t Q B_t^T) C^T + D_t R D_t^T \\
\Sigma_t &= H_t H_t^T \\
x_{t|t} &= A x_{t-1|t-1} + K_t H_t u_t 
\end{align*}
\]

Note that the matrix \( B_t \) is time-varying now. It contains \( \sigma_{zt} \), which controls fundamental uncertainty. The matrix \( D_t \) contains \( \sigma_{st} \), which controls time-varying information friction. Beliefs dispersion is affected by both \( B_t \) and \( D_t \) matrices. Figure 1.8, 1.9 and 1.10 show the beliefs dispersion against \( \sigma_{st} \) and \( \sigma_{zt} \). Beliefs dispersion is a monotonically increasing function of both information uncertainty and fundamental uncertainty.

The model is solved with a 3rd-order perturbation method. Table 1.5 summarizes the full set of parameters used in this model. Most of the parameters remain the same as the
baseline model. Table 1.6 shows the ability of the extended model, with both information friction shock and uncertainty shock, to match business cycle moments. The model matches key moments of the US data closely as reported in the second column. Simulated moments
from the baseline mode and extended model are reported in the third and fourth column. For the simulated data, the table shows the mean values across simulations, along with the 5th and 95th percentile values in brackets. For most of the moments of interest, the range of empirical estimates falls inside the 90 percent confidence intervals generated by the model.

To study the asset pricing implication of this extended model, I focus on the innovations to the log of stochastic discount factor, which characterize the risk compensation in this economy.

\[ m_t - E_{t-1} [m_t] = -\lambda_t^e \epsilon_t^e - \lambda_t^\delta \epsilon_t^\delta - \lambda_t^f \epsilon_t^f - \lambda_t^s \eta_t^s - \lambda_t^a \eta_t^a \]  

(1.55)

I focus on the \( \lambda_t^e \) and \( \lambda_t^a \) terms, which determine the price of risk associated with information uncertainty risk and fundamental uncertainty risk. Similarly, I examine the unconditional mean of \( \lambda_t^e \) and \( \lambda_t^a \).

\[ \bar{\lambda}^e \equiv E [\lambda_t^e] = -0.0025 \]
\[ \bar{\lambda}^a \equiv E [\lambda_t^a] = -0.0025 \]

Both information uncertainty and fundamental uncertainty carry a negative price of risk. A positive shock to the information friction or fundamental uncertainty induces the marginal utility of consumption to increase, i.e. in a bad state of world. On average, the price of risk for one standard deviation shock to the information friction or fundamental uncertainty is
Table 1.5: Parameterization - Extended Model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Preference</strong></td>
<td></td>
<td></td>
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<tr>
<td>Discount factor</td>
<td>$\beta$</td>
<td>0.994</td>
</tr>
<tr>
<td>Risk aversion</td>
<td>$\gamma$</td>
<td>8.0</td>
</tr>
<tr>
<td>Elasticity of intertemporal substitution</td>
<td>$\psi$</td>
<td>2.0</td>
</tr>
<tr>
<td>Leisure exponent in utility</td>
<td>$\theta$</td>
<td>0.36</td>
</tr>
<tr>
<td><strong>Technology</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Capital exponent in production</td>
<td>$\alpha$</td>
<td>0.34</td>
</tr>
<tr>
<td>Depreciation rate</td>
<td>$\delta$</td>
<td>0.025</td>
</tr>
<tr>
<td>Deterministic growth rate</td>
<td>$\mu$</td>
<td>0.0049</td>
</tr>
<tr>
<td>Persistence of permanent productivity shock</td>
<td>$\rho_g$</td>
<td>0.89</td>
</tr>
<tr>
<td>Volatility of permanent productivity shock</td>
<td>$\sigma_g$</td>
<td>0.002</td>
</tr>
<tr>
<td>Persistence of transitory productivity shock</td>
<td>$\rho_z$</td>
<td>0.89</td>
</tr>
<tr>
<td>Volatility of transitory productivity shock</td>
<td>$\sigma_z$</td>
<td>0.015</td>
</tr>
<tr>
<td>Capital adjustment cost</td>
<td>$\xi$</td>
<td>20.0</td>
</tr>
<tr>
<td>Persistence of financial friction shock</td>
<td>$\rho_f$</td>
<td>0.80</td>
</tr>
<tr>
<td>Volatility of financial friction shock</td>
<td>$\sigma_f$</td>
<td>0.04</td>
</tr>
<tr>
<td>Operating cost</td>
<td>$\iota$</td>
<td>0.0018</td>
</tr>
<tr>
<td>Wage adjustment cost</td>
<td>$\xi_w$</td>
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</tr>
<tr>
<td>Persistence of uncertainty shock</td>
<td>$\kappa_a$</td>
<td>0.90</td>
</tr>
<tr>
<td>Volatility of uncertainty shock</td>
<td>$\omega_a$</td>
<td>0.02</td>
</tr>
<tr>
<td><strong>Information Friction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average level of information friction</td>
<td>$\bar{\sigma}_s$</td>
<td>0.0147</td>
</tr>
<tr>
<td>Persistence of information friction shock</td>
<td>$\kappa_s$</td>
<td>0.90</td>
</tr>
<tr>
<td>Volatility of information friction shock</td>
<td>$\omega_s$</td>
<td>0.02</td>
</tr>
<tr>
<td><strong>Correlation</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{Corr}(\eta_t^s, \epsilon_t^f)$</td>
<td>$\varrho^{sf}$</td>
<td>-0.70</td>
</tr>
<tr>
<td>$\text{Corr}(\eta_t^a, \epsilon_t^f)$</td>
<td>$\varrho^{af}$</td>
<td>-0.70</td>
</tr>
</tbody>
</table>

0.25%. Under the assumptions of this extended model, both information uncertainty and fundamental productivity uncertainty contribute 50% to the total uncertainty risk in this economy.

1.7.3 Social Welfare

To examine any policy implication, I plot the social welfare over $[\sigma_{st}, \sigma_{zt}]$ space under average economic conditions in Figure 1.11. High information friction decreases social welfare. A
Table 1.6: Business Cycle Moments - Extended Model

<table>
<thead>
<tr>
<th>Macroeconomic Quantities</th>
<th>Data</th>
<th>Baseline</th>
<th>Extended</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma[\Delta y]$</td>
<td>1.38%</td>
<td>1.53%</td>
<td>1.54%</td>
</tr>
<tr>
<td></td>
<td>[1.41% 1.67%]</td>
<td>[1.41% 1.69%]</td>
<td></td>
</tr>
<tr>
<td>$\sigma[\Delta c]/\sigma[\Delta y]$</td>
<td>0.37</td>
<td>0.61</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>[0.54 0.68]</td>
<td>[0.54 0.68]</td>
<td></td>
</tr>
<tr>
<td>$\sigma[\Delta i]/\sigma[\Delta y]$</td>
<td>3.45</td>
<td>3.40</td>
<td>3.39</td>
</tr>
<tr>
<td></td>
<td>[3.20 3.62]</td>
<td>[3.18 3.64]</td>
<td></td>
</tr>
<tr>
<td>$\sigma[\Delta l]/\sigma[\Delta y]$</td>
<td>0.37</td>
<td>0.67</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td>[0.64 0.72]</td>
<td>[0.62 0.73]</td>
<td></td>
</tr>
<tr>
<td>Asset Prices</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$E[r_t - r_f]$</td>
<td>4.09%</td>
<td>4.23%</td>
<td>4.27%</td>
</tr>
<tr>
<td></td>
<td>[3.65% 4.83%]</td>
<td>[3.41% 5.01%]</td>
<td></td>
</tr>
<tr>
<td>$\sigma[r_t - r_f]$</td>
<td>15.80%</td>
<td>18.50%</td>
<td>18.52%</td>
</tr>
<tr>
<td></td>
<td>[16.74% 20.10%]</td>
<td>[16.58% 20.68%]</td>
<td></td>
</tr>
</tbody>
</table>

Note – The table compares moments of the data to simulated moments from the baseline and extended models. I consider log output growth variability, relative variance of consumption to output, relative variance of investment to output, relative variance of labor to output, equity premium, and equity excess return volatility. Moments of actual data are estimated using quarterly US time series data of GDP, consumption, investment and employment from 1948:I to 2014:IV. Moments of simulated data from the model are at quarterly frequency. I report mean moments, along with the 5th and 95th percentiles across 1,000 simulations, each with a length of 50 years.

clear policy implication is to reduce the information uncertainty and enhance social welfare. Increasing the quality of public news, increasing the accuracy of public reports, increasing transparency, and reducing policy uncertainty are all effective ways to reduce information uncertainty or costs associated with information acquisition in the economy. Reducing information friction is always better because agents make more efficient allocation decisions.

1.8 Conclusion

In an economy with a time-varying imperfect information environment, rational agents’ beliefs, with Bayesian learning, feature time-variant second moments. This creates belief uncertainties from the information channel. I investigate the effect of stochastic information friction by analyzing a DSGE model with Epstein-Zin preferences. In particular, the inter-
action between imperfect information and financial market friction provides an important channel to amplify the effect of information uncertainty. Information friction shocks carry a negative price of risk. This source of risk also harms social welfare by preventing efficient allocation. A policy implication from the model is to reduce information uncertainty or costs associated with information acquisition, thus enhancing market allocation efficiency.

Empirical evidence supports the asset pricing prediction from the DSGE model. I construct an empirical measure to proxy for information friction shocks. Innovation to information uncertainty is a negatively priced source of risk for a wide variety of test portfolios. Cross-sectionally, exposure to information uncertainty risk strongly predicts future asset returns. Firms with high exposure to information friction shock generate significantly lower returns than firms with low information friction shock exposure. The estimated risk premium associated with information friction shock is negative and statistically significant. A mimicking portfolio, IFS factor, generates 6% excess return per annum.
CHAPTER 2

WHAT DRIVES INDEX OPTIONS EXPOSURE?

2.1 Introduction

Options on the market portfolio play a key role in capturing investor perception of systematic risk. As such, these instruments are the object of extensive study by both academics and practitioners. An enormous literature is concerned with modeling the prices and returns of these options and analyzing their implications for aggregate risk, preferences and beliefs. Yet, perhaps surprisingly, almost no literature has investigated basic facts about quantities in this market. How much do investors actually use these contracts, and why?

This study addresses these questions by documenting historical patterns in the aggregate demand for (and supply of) S&P 500-based options. We establish primary properties about the level, trend, and the drivers of variation in index options exposure.

While theories of option demand have been proposed for over 40 years, little is known about why index options are traded in practice.\(^1\) In classical models, derivatives are redundant assets whose quantities are essentially indeterminate. Positive net demand arises with heterogeneous agents in the presence of frictions or market incompleteness. Examining demand patterns empirically may thus be informative about the relevant type and degree of heterogeneity, frictions, and incompleteness. Since index options effectively reference, the 'market portfolio', these elements are potentially primitive features of the economy that may be fundamental in understanding asset pricing.

To guide our empirical investigation, Table 1 summarizes three potentially distinguishable families of theories of option demand. We identify these by the type of risk transfer that motivates the demand (first row) and the nature of the heterogeneity across agents that drives trade (second row). The hypotheses are not meant to be exhaustive. However, they represent distinct economic notions that may suggest differing predictions.

\(^1\)By contrast, a substantial empirical literature starting with Easley et al. (1998) examines quantities of individual firm options, focusing on the role of private information. Recent contributions include Lakonishok et al. (2007) and Roll et al. (2010). One would expect private information to play little role in index options markets.
Table 2.1: Option Demand Hypotheses

<table>
<thead>
<tr>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Risk:</strong></td>
<td>Market risk (spanned)</td>
<td>Unspanned market risk (e.g. jump risk)</td>
</tr>
<tr>
<td><strong>Heterogeneity:</strong></td>
<td>trading costs; portfolio constraints</td>
<td>beliefs; preferences; background risk; portfolio constraints</td>
</tr>
<tr>
<td><strong>Potential covariates:</strong></td>
<td>commissions; spreads; information technology; retail participation</td>
<td>risk measures; volume; disagreement; wealth shares</td>
</tr>
<tr>
<td><strong>Likely preferred types of option:</strong></td>
<td>high elasticity; at-the-money</td>
<td>low strike price</td>
</tr>
</tbody>
</table>

Column (1) describes theories in which options are used to transfer risk associated with the level of aggregate wealth. As discussed by Black (1975) and emphasized by practitioners, options may present a cost or efficiency advantage for such transfer when some agents face frictions like costly borrowing, short-sale constraints, or transactions costs in the underlying market. (This type of demand can exist even under the complete-market assumptions that support classical option pricing theories, since the theories only require that some agents face frictionless markets.) If these factors are important, one would expect variation in options usage to correlate with variation in measures of transaction costs. Moreover, since these costs are highest for individuals, options usage might be expected to vary with the level of retail participation.

Since at least Ross (1976) and Hakansson (1978) economists have appreciated that perfect markets fully spanned by the ability to trade in an underlying index asset is an abstraction, and that options may therefore play a real role in completing markets. Much work has focused on the case of jump-diffusion processes, emphasizing the role of options as hedges for downside jumps (i.e., crashes). But even a simple two-period economy (as in Grossman and Zhou (1996)) there will be unspanned risk with more than two market outcomes.
The second column (2) describes theories of this type. There is a very broad range of models, both partial and general equilibrium, encompassing investors who differ on a number of different dimensions.\(^2\) Most work considers heterogeneity in beliefs or preferences. But demand can also be driven by differences in such factors as background risk or portfolio constraints, which may be indistinguishable from preference differences.\(^3\)

Column (3) describes models also concerned with the transfer of unspanned risk, but not of the market return itself, but of the return’s second (or higher) moments. Models of unspanned stochastic volatility have been used in practice since the 1980s. More recently, much work in asset pricing has explored the implications of nonstandard preference theories, such as those of Epstein and Zin (1989), in which agents’ utility may directly depend on higher-order risks. As with column (2), this type of unspanned risk could be combined with numerous types of heterogeneity to generate net option demand.\(^4\)

For either type of unspanned risk transfer (columns (2) and (3)), a natural hypothesis is that the quantity of options should fluctuate with the degree of risk.\(^5\) Our empirical work will employ a number of recently developed proxies for different dimensions of economic risk. Similarly, measures that reflect changes in the degree of heterogeneity of the investor population may explain option usage. We have some candidate proxies for disagreement, sentiment (or risk-aversion). Moreover, with any type of heterogeneity, the degree of trade will vary with the relative wealths of the subsets of agents who are trading. We examine time variation in the composition of the U.S. investor population (households versus different institutions) as a potential driver of options trends.

Finally, the last row of the table is motivated by the observation that different reasons for option usage will be reflected in different types of options being preferred by investors. For example, if cost considerations in gaining market exposure are an important factor, then investors may prefer options with maximum elasticity ("bang for the buck") either on the long or short side. Alternatively, they may prefer options whose liquidity is highest, which are typically those at-the-money. By contrast, if investors are concerned with unspanned crash risk, demand would be expected to be concentrated in out-of-the-money puts. Whereas, if volatility risk transfer is an important motivation for trade, one might expect that most

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\(^3\)See Franke et al. (1998) and Vanden (2004).

\(^4\)Recent models of heterogeneity in perception of (and/or aversion to) stochastic volatility or time-varying disaster risk include Bates (2008) and Chen et al. (2012).

\(^5\)Since Rothschild and Stiglitz (1971), a large body of work has explored conditions under which demand for insurance increases with risk. See also Eeckhoudt and Gollier (2000). With both supply and demand effects, the sign of the effect on quantity is indeterminate.
activity would be in long-dated options, whose volatility sensitivity ("vega") is highest.

To be clear, the goal of our study is to let the data speak to us on high-level issues, as suggested by the table. We do not aim to structurally test particular models, few of which have been developed to the point where they might reasonably be brought to the data. (And, as discussed above, many distinct models may, in fact, have similar empirical implications.) Instead, we view our contribution as laying the groundwork for future theoretical and empirical work on this topic.

For econometric clarity, our work proceeds by first documenting the scale of the index options market, then modeling its stochastic trend, and finally explaining variation from that trend. Our findings may be summarized as follows.

The overall size of the options market is small in terms of the aggregate value of contracts and their gross exposure to volatility risk. On the other hand, the market is large in the sense that market jumps have the potential to induce substantial exposures and economically large rehedging demands. Our findings about market scale appear to be robust to consideration of over-the-counter (OTC) derivatives, non-US contracts, and listed volatility derivatives.

Examination of options usage by type reveals that almost half of open interest is concentrated in out-of-the-money puts. This is strong evidence in favor of the unspanned crash-risk story for options usage. By contrast, volatility risk transfer would appear less important, as long-dated, at-the-money options (i.e., those with high volatility exposure) are a small component of open interest.

Over time, the scale of positions in index options is nonstationary. The outstanding number of contracts was quiet in the mid 1990s, rose substantially prior to 2007 and has since stagnated. The nonstationarity is well explained by the stochastic trend in stock market turnover, affirming the intuition above that trading volume impounds both the degree of investor heterogeneity and the evolution of financial transactions technology. On the other hand, we do not find that changing composition of the investor population can account for the evolution of options usage. Nor do the level of interest rates and information technology costs account for the trend in options positions.

The most significant determinant of fluctuations in detrended options positions is a negative response to risk, which is not driven by the risk-aversion component in measures of investor sentiment, nor by differences of opinion. Increases in belief dispersion and deterioration of investor sentiment induce significant positive responses of aggregate open interest. There is also evidence of a positive quantity response to some measures of tail risk.

The primary finding of a strong negative response to risk is suggestive of a story in which one set of agents (e.g., dealers) have tolerance for unspanned crash risk that is higher than
that of another class (e.g., investors) in normal times, but which diminishes rapidly in the
face of rising risk, possibly due to binding position constraints or wealth effects.

In all, we succeed to a large degree in answering the question in the paper’s title: our
empirical descriptions of aggregate options measures achieve high explanatory power. Fluc-
tuations in equity market activity and different dimensions of risk drive most of the variation
in options quantities.

The outline of the paper is as follows. The next section reviews the products with which
the study will be concerned, addresses some conceptual issues in the measurement of options
positions, and describes our aggregate exposure variables. Section 3 presents our basic
findings for levels and economic magnitude of options quantities. Section 4 addresses the
trend in the data via a cointegration analysis with potential nonstationary factors. Section 5
then investigates determinants of deviations from the fitted trend. A final section summarizes
the findings and highlights issues for future research that our study raises.

2.2 Measuring Index Options Quantities

This section describes the options series that we construct and discuss some conceptual issues
in aggregation. We also describe the most important sources of exposure that our measures
do not capture.

Options on stock indexes have traded on exchanges in the U.S. since the early 1980s. Our
goal is to study historical trends in this activity, and therefore we focus on a single underlying
index – the S&P 500 – to ensure consistency over time. We are thus omitting options on
other indexes that have, at one time or another, enjoyed a degree of popularity.\textsuperscript{6} Even
within the set of products referencing the S&P 500, there has been a lot of variation in, and
competition among, the products available for trade and their relative market shares. Our
data consists of three classes of products, whose differing trade and settlement mechanism
makes them not literally fungible, but which are essentially equivalent economically, allowing
us to aggregate our measures across them. The products we use are the following:

- CBOE S&P 500 Index (SPX) Options.
- CME S&P 500 Futures Options.
- Options on SPDR ETFs (SPY).

\textsuperscript{6}Today the most liquid U.S. index products other than those referencing the S&P 500 are those on the
NASDAQ 100. Other index products that have been important in the past include those on the Value Line
index, the AMEX Major Market index, the Dow-Jones 30, the Russell 5000, and the S&P 100.
Appendix A.1 provides institutional details on each of these contract types and on the data we have for each.

As described in the introduction, our interest is in quantifying the extent of demand for index options as a distinct product class. At this point, it is worth considering conceptually what it is that we would ideally like to measure. There are two important issues.

First, options obviously are not interchangeable. So how should positions of different types be aggregated? In particular, call and put positions represent opposite exposures to index returns. Our view is that the economically interesting feature of options positions is the nonlinearity that is common to both products however. We are not attempting to measure directional exposure. Therefore we will treat puts and calls interchangeably, and sum their gross positions. As a robustness check, and to gain further insight into demand characteristics, we will also report results for separate buckets of options classes (calls/puts; at/in/out of the money; short/long expiration horizon).

Obviously, our measures will be of gross positions, since net options positions are always identically zero. This brings us to the second important issue in aggregation: hedging. Our data are comprehensive over time and across products, but they contain no information on net holdings of particular investors or investor class. We have no way of quantifying the extent to which participants may cancel the economic exposures of their options positions. For example, if a dealer buys a put and sells a call of the exact same expiration and maturity, and then goes long the underlying asset, he effectively has no position in either option. Similar remarks apply to options spread trades – being long and short similar but not identical options.

Since clearly many options markets participants hedge to some degree, this means that our exposure measures may overstate actual economic exposures. However, this caveat itself requires a caveat. Not all kinds of hedging distort the interpretation of gross exposures. In particular, delta hedging – cancelling the directional risk of an options position – is not problematic for us as it leaves intact the essential “option-ness”, or convexity, of the position. For example, if a market participant buys a zero-delta straddle, we do want to measure that as an open position.

7There are data sets of option trade by customer type covering some of our index contracts during some periods. These can shed direct light on questions of why specific investors trade specific types of contracts. See Garleanu et al. (2009), Chen et al. (2014) and Lemmon and Ni (2014) for recent contributions in this direction.

8Our data do, however, take into account literally off-setting positions. All the options in our study are centrally cleared. Reported open interest is netted by the clearing house at the account level. If a market maker buys an option from one customer and sells the exact same option to another, then, the recorded position is the same as if the two customers had traded with each other. This is typically not the case in over-the-counter (OTC) derivatives markets. We discuss OTC markets further below.
Moreover, hedging by one party to an options trade does not by itself nullify the economic impact of the position. It may merely transfer it to whomever the hedging trade is done with. If a dealer buys a call (and sells the underlying) to hedge a short put position, certainly he is effectively out of the position. But unless the call and put position are both with the same counterparty, then someone has assumed the convexity of the original position by selling the put. And, again, we would want to measure that. In the extreme case, it is possible that all options market participants hedge all their convexity (i.e. with each other). But presumably this class of derivatives would not exist if there was not some underlying demand for the nonlinearity of the exposure they afford.

We can now describe the exact construction of the main measures that we will study. Our primary benchmark is simply gross open interest, which provides a non-monetary measure of the total amount of options outstanding. This is calculated as

$$OI(t) = \sum_i CM_i OI_i(t), \quad (2.1)$$

where $CM_i$ (contract multiplier) denotes the number of equivalent index units referenced by a single option of $i$’s type, $OI_i(t)$ (open interest) is the number of option of $i$’s type outstanding on date $t$, and the sum runs over all option types. This measure is in index equivalent units, or “shares” of the S&P 500. Multiplying $OI(t)$ by the level of the index on date $t$ gives a measure of the total monetary value of shares underlying all outstanding options. The latter is effectively the definition of the “notional value” of these derivatives. A second basic measure of outstanding options is simply their aggregate market value, or:

$$MV(t) = \sum_i CM_i OI_i(t) P_i(t). \quad (2.2)$$

where $P_i(t)$ is the closing price of the $i$th option-type. This measure is in units of dollars. It quantifies the gross investment of agents in this product. If all options were somehow voided (e.g., through a clearing-house default) or expired worthless this is the amount that would be lost. Since option values all scale with the level of the underlying, this measure, when compared to the monetary value of the index itself, yields a normalized average contract value.

To measure the gross risk characteristics of options positions, we next introduce two weighted average measures: aggregate vega and aggregate gamma of outstanding contracts.

A standard quantification of the volatility exposure of an option, “vega” is market parlance for the change in the option’s value – according to a benchmark model – when the underlying
annualized volatility is perturbed by 0.01 (one “vol”). If \( v_i(t) \) represents the partial derivative of the \( i \)th option-type (underlying, strike, expiration) on date \( t \), then our aggregate measure is:

\[
AV(t) = 0.01 \sum_i CM_i \ OI_i(t) \ v_i(t).
\] (2.3)

We follow market practice here, using benchmark Black and Scholes (1973) or binomial models for European and American options respectively. By definition, \( v_i(t) \) measures the change in the option’s value in response to a change in implied volatility. We note that this is not necessarily how much the option’s value will change in response to a change in actual return volatility. However, \( AV \) does give a direct quantification of the gross amount of volatility risk transfer achieved in the index options market. Like \( MV \) it is in dollars.

Similarly, “gamma” is market parlance for the model-based sensitivity of the equivalent share exposure (the “delta”) of an options position to a $1 move in the underlying index. We convert this to an equivalent change per 1% move in the underlying via multiplying the partial derivative, \( \Gamma_i(t) \), by \( .01S(t) \) and then summing:

\[
AG(t) = 0.01 \sum_i CM_i \ OI_i(t) \ \Gamma_i(t) \ S(t).
\] (2.4)

This measure gives the total index equivalent units that would have to be traded (in absolute value) if all options positions were re-hedged to market neutrality in response to a one percent index change. It can be expressed as a turnover ratio by dividing by the total index equivalent units outstanding, defined to be simply the total monetary value of the index stocks (weighted by their index share) divided by the level of the index. As described in the next section, \( AG \), can also be related to the total monetary exposure of options positions to the risk of a jump in the index.

Before turning to the data, it is worthwhile to consider briefly what can be said about stock index options not captured by our measures.

We have already alluded to various other U.S. listed index options that have not been consistently successful. However, it is reasonable to wonder how important they might be collectively. The same question could be asked about index options products listed on non-U.S. exchanges, referencing the Nikkei 225 or the FTSE 100 for example. Finally, there are active non-listed OTC index options markets that are not in our measures.

For aggregate information on all of the above products, we will compare our numbers to those reported in a semi-annual survey undertaken by the Bank for International Settlements.

\footnote{The computation is numerically challenging for large numbers of American options. Details of an efficient numerical procedure are given in the appendix.}
(BIS) since 1996. The BIS numbers for exchange-traded options are computed from sources similar to ours, whereas the OTC numbers are estimated based on reports to the BIS from member central banks.\textsuperscript{10} There are issues in comparing OTC numbers to exchange-traded ones. In particular, OTC positions are rarely netted, and are typically cleared bilaterally. This means that amounts outstanding are greatly overstated compared to the equivalent numbers from exchanges. Moreover, the BIS does not correct for double counting of options positions open between reporting banks. This contributes further to the inflation of OTC statistics.\textsuperscript{11} For these reasons, it would be inappropriate to literally combine our measures with the BIS numbers.

Finally, to the extent that our study is concerned with volatility risk transfer, a question arises as to what extent participants have utilized direct volatility derivatives to accomplish this. Investment banks have actively quoted market in variance swaps and other similar products for at least the last 20 years. Unfortunately, we do not know of any sources of data on quantities of OTC volatility derivatives. However recent years have seen a rise in popularity of listed volatility derivatives, especially futures tied the CBOE implied volatility index, VIX. We have data on these contracts, and we discuss their magnitude in the next section.

### 2.3 The History of Index Options Quantities

Figures 2.1-2.4 plot the time series of our measures, showing the contributions of the three contracts separately. (The plots are in logarithms.) By all measures, the dominant class has been the CBOE SPX options. Futures options achieved nearly equal market share briefly in the mid 1990s but have since fallen back. The SPY contracts have grown rapidly and now rival the CME products in terms of open interest and gamma, although their monetary value and vega remains negligible.

All the series are clearly nonstationary. There has been a strong upward trend historically. However there have also been extensive periods of stagnation, including the later 1990s and the period following the financial crisis. We attempt to identify exogenous drivers of these trends in the next section.

In terms of economic magnitudes, the numbers reveal an interesting contrast: the options market is small in monetary value, but large in terms of potential value as measured by

\textsuperscript{10}The survey originally covered banks in the G10 countries, and currently covers 13 countries. The coverage within countries depends on the reporting requirements of each central bank.

\textsuperscript{11}To give a numerical example, suppose Dealer A sells a customer a quantity Q of an option, and buys an offsetting position from Dealer B. Then the BIS survey will see this as open positions of 3Q – 2Q reported by A and 1Q by B. In a centrally cleared market the open interest would be recorded as Q.
Figure 2.1: Total Open Interest

The top line is the total open interest of all outstanding SPX options listed on the CBOE. The middle line is the open interest of all CME-listed options on S&P 500 futures. The lowest line is the open interest of all options on SPDR ETFs. The units are logarithms of index equivalent units.

The number of shares referenced. Table 2.2 reports the series values as of the end of the sample 12/31/2012 as well as on the highest recorded day of AV which was 9/22/2008. For reference, the first and fourth columns give the size of the S&P 500 in (respectively) billions of dollars and billions of equivalent shares outstanding. (The latter is defined as the former divided by the nominal index level.)

From the second column, the total value of all S&P 500 options is less than $100 billion, about the scale of a single mid-sized company. The capitalization of the market itself is two orders of magnitude larger. In terms of risk transfer, the vega numbers in the third column indicate that, again, investors have not insured much exposure. An aggregate vega value of $2 billion means that a doubling of return volatility, e.g. from 20% to 40%, would transfer an economically negligible $40 billion from option writers to option purchasers.

On the other hand, from the fifth column, the number of shares referenced by index options are a nonnegligible fraction of the total equity of the market. The small monetary value and vega, then, are indications that most option positions are short-term and/or out-of-the-money. The sixth column indicates that aggregate gamma is high in the sense that a one percent move in the market could induce rehedging demands that correspond to approximately one percent of shares outstanding. This may not seem large until one recognizes that total turnover of the U.S. equity markets averages well less than one percent
The top line is the total market value of all outstanding SPX options listed on the CBOE. The middle line is the market value of all CME-listed options on S&P 500 futures. The lowest line is the market value of all options on SPDR ETFs. The units are logarithms of dollar value.

of shares outstanding on any given day. Thus options positions are quite large economically in terms of their potential to transfer risk. While we know it is not the case, as emphasized above, that long options positions and short option positions are held by disjoint sets of agents, even if only a fraction induce rehedging, the response to, say, a 10 percent index move could strain market liquidity.\footnote{Of course, if long and short gamma players both maintain delta-neutral positions, then their rehedging demands would offset, i.e., they could always trade with each other. In practice, market-makers – who tend to be short gamma – are more likely to rehedge than are end users.}

Table 2.3 shows the average fraction of open interest represented by 12 types of option: calls and puts, separately classified as short or long term depending on whether the expiration is under or over 40 days away, and classified as in-, at, or out-of-the-money based on Black-Scholes delta cutoffs (in absolute value) of 0.375 and 0.625. (The table restricts attention to the dominant SPX class of options.)

Investor positions are concentrated in out-of-the-money puts. As of the end of the sample these constituted more open interest (51 \%) than all other types combined. Note that, by put-call-parity, the exposure transferred by low strike calls is essentially the same as that of low strike puts.

While longer term options represent about two thirds of open interest, short term options are traded about twice as often relative to their open interest. This is shown in the second
The top line is the total volatility sensitivity of all outstanding SPX options listed on the CBOE. The middle line is the volatility sensitivity of all CmME-listed options on S&P 500 futures. The lowest line is the volatility sensitivity of all options on SPDR ETFs. The units are logarithms of dollar value per 100 basis point change in annualized volatility.

The picture of a market dominated by low strike price put positions is consistent with index options being used primarily for crash insurance. Indeed, the amount of crash insurance can be quantified with our aggregate gamma numbers. For any position hedged with respect to market direction, the leading term in a Taylor series expansion for the change in position value in response to a jump of size \( j \) is

\[
\frac{1}{2} \Gamma j^2
\]

where \( \Gamma \) is the second partial derivative of the position value with respect to the underlying. Aggregating this quantity as of December 2012, Figure 2.5 shows the potential monetary transfer as a function of the jump percentage. For moderate jumps, the number is in the hundreds of billions of dollars and approaches trillions for a severe crash. In fact, in the case of a downward jump this number is an understatement since we know from above that most open positions are out-of-the-money puts. The graph also shows the change in position value when the aggregate position is approximated as a three-month put with strike chosen to
Figure 2.4: Aggregate Gamma

The top line is the total delta sensitivity of all outstanding SPX options listed on the CBOE. The middle line is the delta sensitivity of all CmME-listed options on S&P 500 futures. The lowest line is the delta sensitivity of all options on SPDR ETFs. The units are logarithms of index equivalent units per one percent index change.

We find that our study is not missing any significant U.S. listed index options. Similarly, given the overcounting of OTC positions, the U.S. OTC index exposure not captured in our data, while substantial, is at least not larger than the ones we

\[ \text{Notional amounts} = OI(t) \times S(t) \]

The numbers in the table show that our study is not missing any significant U.S. listed index options. Similarly, given the overcounting of OTC positions, the U.S. OTC index exposure not captured in our data, while substantial, is at least not larger than the ones we

\[ \text{Notional amounts} = OI(t) \times S(t) \]

In practice, OTC participants may report the notional amount as the value of the underlying stock on each option at the exercise price. For example, the right to buy $100 million dollars of stock at price $K$ would be equivalent to a listed option on $100$ million-divided-by-$K$ units which we would record as a notional amount of $(S/K)$ times $100$ million, whereas OTC participants may report $100$ million as the notional value.

\[ \text{Notional amounts} = OI(t) \times S(t) \]

The fact that our contracts appear to exceed the size of a set that strictly includes them may be due to timing differences in data collection.

---

\[ \text{Notional amounts} = OI(t) \times S(t) \]

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\[ \text{Notional amounts} = OI(t) \times S(t) \]
Table 2.2: S&P 500 Options Quantities

<table>
<thead>
<tr>
<th></th>
<th>MV</th>
<th>AV</th>
<th>OI</th>
<th>AG</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPX</td>
<td>34.75</td>
<td>1.456</td>
<td>0.909</td>
<td>0.0264</td>
</tr>
<tr>
<td>futures</td>
<td>1.85</td>
<td>0.142</td>
<td>0.136</td>
<td>0.0046</td>
</tr>
<tr>
<td>SPY</td>
<td>0.38</td>
<td>0.023</td>
<td>0.183</td>
<td>0.0675</td>
</tr>
<tr>
<td>total</td>
<td>13121</td>
<td>36.98</td>
<td>1.621</td>
<td>9.200</td>
</tr>
</tbody>
</table>

The table reports option quantity measures on two dates. For comparison, the first and fourth columns give the capitalization of the S&P 500 (in billions of dollars) and the effective number of index shares outstanding (in billions of index units) defined as the capitalization divided by the index level. Market value (MV) and aggregate vega (AV) are in billions of dollars. Open interest (OI) and aggregate gamma (AG) are in billions of index-equivalent units.

The previous section also noted the emergence of listed derivatives on stock market volatility as a related and possible substitute product class. While volatility and variance swaps have been actively traded in OTC markets for at least ten years, the first exchange-traded products were cash-settled futures tied to the VIX index introduced in 2004. For unclear reasons, investor interest in these products – and their liquidity – took off in the last few years. By the design of these contracts, their open interest is directly comparable to our AV measure of volatility exposure in the index options market.

Figure 2.6 shows our aggregate vega series both alone (solid line) and with the additional total vega of the futures (dashed line) since 2009. As of the end of the sample, the difference in the series is around 0.25, meaning that the futures account for about a fifth of the total volatility exposure. We conclude that this exposure is comparatively substantial (and rapidly growing), but is still small in economic magnitude.

16We are unaware of data series on quantities of OTC volatility derivatives.
Table 2.3: S&P 500 Options Quantities by Type

<table>
<thead>
<tr>
<th>Fraction of open interest</th>
<th>low strike</th>
<th>at-the-money</th>
<th>high strike</th>
</tr>
</thead>
<tbody>
<tr>
<td>calls, long-term</td>
<td>0.0742</td>
<td>0.0660</td>
<td>0.1067</td>
</tr>
<tr>
<td>calls, short-term</td>
<td>0.0538</td>
<td>0.0206</td>
<td>0.0762</td>
</tr>
<tr>
<td>puts, long-term</td>
<td>0.2939</td>
<td>0.0597</td>
<td>0.0345</td>
</tr>
<tr>
<td>puts, short-term</td>
<td>0.1668</td>
<td>0.0196</td>
<td>0.0281</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Average volume over change in open interest</th>
<th>low strike</th>
<th>at-the-money</th>
<th>high strike</th>
</tr>
</thead>
<tbody>
<tr>
<td>calls, long-term</td>
<td>1.11</td>
<td>1.74</td>
<td>1.67</td>
</tr>
<tr>
<td>calls, short-term</td>
<td>2.95</td>
<td>2.98</td>
<td>3.23</td>
</tr>
<tr>
<td>puts, long-term</td>
<td>1.78</td>
<td>1.90</td>
<td>1.23</td>
</tr>
<tr>
<td>puts, short-term</td>
<td>3.17</td>
<td>3.10</td>
<td>2.78</td>
</tr>
</tbody>
</table>

The top panel table reports the average fraction of aggregate open interest in CBOE-listed SPX options comprised of calls and puts; long (over 40 days) and short time to expiration; and strike prices below, near, or above the current index level. The strike price breakpoints are determined by the Black-Scholes delta of the respective options, with low strike puts having delta greater than -0.375, low strike calls having delta greater than 0.625, high strike puts having delta less than -0.625, high strike calls having delta less than 0.375. The bottom panel shows time series averages of each month’s ratio of volume to absolute change in open interest. The sample period is 1/5/1990 to 12/31/2012.

2.4 The Stochastic Trend in Options Exposure

We now turn to the question of characterizing the trend driving the evolution of options exposure. An initial observation about the four series is that the stochastic component appears to be common among them. If we express the gamma, vega, and market value series on a per-contract basis by dividing by open interest, and also normalize the latter two series by also dividing by the index level\(^{17}\), the resulting series (shown in logs in Figure 2.7) appear stationary. Standard tests for unit roots reject the null of nonstationarity, consistent with the visual impression.

From this analysis, it follows that the composition of the options outstanding in terms of their convexity and market value is relatively stable over time. We can, therefore, focus our attention on a single quantity series – aggregate open interest – in modelling the nonstationary component of options positions. Note that \(OI\), measured in index-equivalent units, is not mechanically related to the level of the stock market or its volatility.

In seeking to explain the stochastic trend in \(OI\), we refer to the hypotheses outlined in the

\(^{17}\text{Option values and vegas scale mechanically with the level of the underlying. With our unit definition of gamma, that series does not scale with the underlying.}\)
introduction and consider possible trends in investor heterogeneity and/or market frictions. Here a natural prior hypothesis is to link options market trends to trends in other measures of financial activity that are likely to be driven by the same forces. In particular, equity market trading volume should also reflect differences in preferences and beliefs, as well as trends in trading costs and technology in the financial industry. To formally assess the hypothesis, we perform cointegration tests using the log of median daily turnover, $TO$, of stocks whose primary listing is on the NYSE and American Stock Exchange.\footnote{The volume measures encompass trading consolidated across all exchanges, trading platforms, dark pools, etc. The turnover series is computed as a trailing 21-day average, dropping days adjacent to holidays.}

While detrending $OI$ with equity market turnover will turn out to be successful, it does raise the question of what drives turnover. That topic is itself an important open question that is beyond the scope of the present work. However, it is reasonable to ask whether the evolution of options exposures can be associated more directly with measures of population heterogeneity or investment frictions. We propose a few ideas.

One hypothesis is that an important dimension of heterogeneity is of the type of investors or institutions that are active in the market. Rather than attempt to find proxies for unobservable preferences or beliefs, this approach posits that these characteristics may be common to a class of participants. Demand for and supply of options may then be associated with changes in the relative size of different types of participants. We assess this hypothesis using data from the Federal Reserve’s quarterly $Z.1$ reports on ownership of U.S. corporate equity. From these, we construct the market share of five classes of participants: households, mutual
<table>
<thead>
<tr>
<th>Notional Amount Outstanding (USD billion)</th>
</tr>
</thead>
<tbody>
<tr>
<td>listed S&amp;P 500</td>
</tr>
<tr>
<td>Dec, 2012</td>
</tr>
</tbody>
</table>

The table reports outstanding amounts of equity index options as of December 2012. The first column aggregates the contracts used in this study, and is a daily average over the month. The remaining columns are from the BIS semi-annual derivatives surveys: [http://www.bis.org/statistics/derstats.htm](http://www.bis.org/statistics/derstats.htm). For the second and third columns, the U.S. numbers include North American exchanges. The OTC columns count all equity options not just those referencing indices.

**funds and ETFs, pension and insurance funds, foreign institutions, and brokerage firms and securities dealers.** Shares of equity ownership are, of course, not direct measures of the population of index options market participants. But it is certainly plausible that trends in the two are closely related. Our tests assess whether the trend in $OI$ is explained by the trend share of any one of the five types.

Next, we consider potential measurement of investment frictions. Over the sample period, the cost of transacting in the stock market declined dramatically for most investors due to a combination of cheaper information processing, data availability, and competition among intermediaries. Commissions and direct trading costs have trended strongly downwards while market liquidity has trended upwards. Borrowing costs, another potential constraint on trading activity, also trended strongly downward during the sample period.

Note that the theoretical prediction here would be that options demand would **decline** with interest rates if investors use options precisely because of their embedded leverage. Likewise, to the extent that the underlying markets for index stocks become cheaper to trade, it becomes easier to replicate any nonlinear payoff achievable with options, suggesting a decline in demand. On the other hand, clearly cheaper options trading itself would be expected to increase options usage. Similarly improvements in trading infrastructure to lower technological barriers to trading options should promote usage.

With these considerations in mind, we include in our analysis a measure of average trading costs in the options market, a general information processing proxy, and the 3-month eurodollar interest rate. The trading cost proxy is an average of closing percentage bid/ask spreads for the CBOE SPX options. The technology variable is an index of the cost of household information technology, hardware and services compiled by the Bureau of Labor Statistics (BLS).
The lower dashed line is the aggregate vega of listed S&P 500 options. The solid line includes the contribution of listed futures on the VIX index. The units are logarithms of dollar exposures.

For each of the variables described above, we undertake a series of bivariate cointegration tests with the time series of the log of aggregate open interest. Table 2.5 shows the resulting test statistics for the null of no cointegration. Rejections are thus evidence of a common stochastic trend.

The tests show positive evidence of a common stochastic trend between $OI$ and $TO$, but no evidence that any of the other variables shares a common trend with $OI$.\footnote{The Johansen statistics for the bid-ask series and the pension and insurance share are misleading because this test considers arbitrary combinations of the two variables. Here the estimated weighting on $OI$ in the cointegrating vector is actually zero. The test is simply saying that the other two series on their own look stationary. By contrast, the other two test statistics are based on regression residuals that take $OI$ as the dependent variable. The remaining variables examined in the table all pass standard unit root tests.} Evidently, the remaining variables fail to capture relevant dimensions of heterogeneity or costs that affect options activity. The explanatory power of turnover cannot, then, be attributed to these factors.\footnote{This conclusion is robust to consideration of multivariate cointegrating relationships. Results are omitted for brevity.}

While it remains an important and interesting topic to explain what exactly equity market turnover is capturing, for present purposes the conclusion is that the same trend driving it also drives options usage. Is reverse causality a possibility? We previously documented that the scale of options position was large enough to potentially induce substantial equity trade (via rehedging of delta-neutral positions). We are not able to measure actual options hedging trades in the stock market. However we can measure trading that is not plausibly

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure2_6.png}
\caption{Listed Volatility Futures}
\end{figure}
attributable to index options: namely, activity in non-index stocks. When we construct our turnover measure using exclusively these stocks, the cointegration results are stronger than those reported in the table.\textsuperscript{21} It is thus reasonable to conclude that the exogenous component of equity market activity drives options positions.

To close this section, we consider whether our conclusions about the driving trends in options exposure are likely to be sensitive to the omission of data from the OTC market. Figure 2.8 compares the evolution of our aggregate open interest series with that of the OTC series from the BIS, when the latter is expressed in terms of equivalent S&P 500 units. (Both series are in logs.) The two series track each other quite closely from 1998

\textsuperscript{21}All three tests statistics reject at the 99\% level. Results are available upon request.
Table 2.5: Cointegration Analysis of Aggregate Open Interest

<table>
<thead>
<tr>
<th>Variable</th>
<th>Phillips-Perron:</th>
<th>Engle-Granger:</th>
<th>Johansen:</th>
</tr>
</thead>
<tbody>
<tr>
<td>log TO</td>
<td>-4.44***</td>
<td>-3.63**</td>
<td>14.70*</td>
</tr>
<tr>
<td>s_{household}</td>
<td>-1.57</td>
<td>-1.57</td>
<td>6.41</td>
</tr>
<tr>
<td>s_{funds}</td>
<td>-1.46</td>
<td>-1.19</td>
<td>5.37</td>
</tr>
<tr>
<td>s_{pens+ins}</td>
<td>-2.03</td>
<td>-2.01</td>
<td>14.74*</td>
</tr>
<tr>
<td>s_{broker}</td>
<td>-1.12</td>
<td>-1.04</td>
<td>10.01</td>
</tr>
<tr>
<td>s_{foreign}</td>
<td>-2.09</td>
<td>-1.90</td>
<td>9.71</td>
</tr>
<tr>
<td>bid/ask</td>
<td>-1.52</td>
<td>-1.12</td>
<td>26.28***</td>
</tr>
<tr>
<td>CPI_{info}</td>
<td>-1.96</td>
<td>-1.43</td>
<td>11.80</td>
</tr>
<tr>
<td>r_{3mo}^{ED}</td>
<td>-0.69</td>
<td>-0.43</td>
<td>7.44</td>
</tr>
</tbody>
</table>

The table reports results of three cointegration tests for bivariate systems, the first element of which is the log of the aggregate open interest in list S&P 500 options and the second element is the variable shown in the first column. TO is the median daily turnover for the prior month of stocks whose primary listing is the NYSE or AMEX. The investor composition variables, s, are the relative shares of each category in total U.S. equity ownership as of the end of the previous quarter. bid/ask is the open-interest weighted average closing percentage bid/ask spread of CBOE SPX options. CPI_{info} is the real household cost of information technology, hardware and services compiled by the BLS. r_{3mo}^{ED} is the 3-month eurodollar interest rate. The second column gives the test statistic for the test of Phillips-Perron (1988); the third column gives the test statistic for the Engle-Granger (1988) test; the fourth column shows the Johansen (1991) trace test statistic. One, two, and three asterisks denote rejection of the null of no cointegration at the 90%, 95% and 99% thresholds, respectively. All tests use three months of daily lags. The sample period is January 5, 1990 to December 31, 2012.

through 2006, coincidentally almost being equal in magnitude. However there has been a pronounced erosion in the OTC market share in recent years. In raw terms, the OTC market now accounts only half as much net notional exposure as the exchange-traded products.\(^{22}\)

The graph suggests that combined index options positions from the two venues may have declined more since 2007 than our exchange-traded series alone indicates. On the other hand,
The two series do move more-or-less in parallel from 2008 onwards. Thus we conclude that our conclusions about the broad trends since 1990 are unlikely to be biased by the absence of OTC data.

We have now answered an important part of the question in the paper’s title. There are noteworthy findings, both positive and negative. We do not find support for theories that posit that options usage is driven by borrowing constraints or relative transactions costs vis a vis the underlying market. Nor are we able to associate options quantities with a particular class of investor participation. Instead, we find the stochastic trend that drives options positions is well described by that of equity market turnover. We have posited that the latter trend reflects trends in heterogeneity in beliefs or preferences, as well as the cost of trading. Substantiating that conjecture remains a topic for future research.

2.5 Risk and Index Options Quantities

We now turn to the topic of modelling options quantities in terms of their deviation from the stochastic trend documented in Section 2.4. As discussed in the introduction, theoretical considerations imply that the amount of risk transfer should vary with the degree of risk. We therefore consider here a number of measures of different types of risk.

The dependent variable in this section is the stochastically detrended log open-interest
series. Specifically, the full-information maximum likelihood (FIML) estimator for the cointegrating coefficient in the Johansen (1991) estimation is approximately 1.70. So the finding above is that \( \log OI - 1.7 \log TO \) is stationary. It is this difference that we study here.\textsuperscript{23} Our analysis reports results of levels regressions. These are consistent under the null of stationarity.\textsuperscript{24} As a robustness check, in Appendix A.3, we report results of nonstationary regressions in which turnover is on the right-hand side.

To start, we consider measures of investor perception of risk. We have two convenient time series that characterize the most important features of the S&P implied volatility surface since 1990. The well-known VIX series (the so-called new version) provides a model-free estimate of risk neutral expected volatility for the next 30 days. More recently, the CBOE has also constructed an analogous model-free estimate of the skewness of implied volatility.\textsuperscript{25} Since this skewness is typically negative (i.e. the return distribution is left-skewed) the CBOE value has a minus sign in the definition. Moreover it is a measure of standardized skewness. That is, the variance has been scaled out of it: the correlation of VIX and SKEW is -0.05. This is by construction. A SKEW value of 120, for example, indicates intuitively that there is 20% more mass in the left tail than the right tail. It does not indicate an absolute amount of probability in the left tail. We therefore interact VIX and SKEW to capture the latter information as well.

Table 2.6 presents regressions of detrended log open-interest on these variables. The first row shows that there is a significantly negative response of options quantities to VIX. This effect is economically large. All variables are in logs, and the standard deviation of VIX is approximately 0.35. So, using the smallest coefficient in the first column, a one standard deviation increase in VIX implies a 15% decline in open interest, and this alone explains over 20 percent of the variability in \( OI \).

When SKEW is included, in the second column, it too enters with a negative response, although insignificantly. However this becomes very significant when the interaction term is included (third column). The interaction of VIX and SKEW is positive and highly significant, meaning that for large values of either variable, the marginal response to the other will be positive. Figure 2.9 plots the two dimensional response surface over a range of approximately \( \pm 3 \) standard deviations of both independent variables. From the scale of the vertical axis, the effects are economically large. For reference, the standard deviation of the dependent

\textsuperscript{23} The series still contains a strong seasonal component, notably shrinking over the 4th quarter of each year and rebounding in the 1st quarter. We remove this component in the regression analysis below by subtracting the full-sample average growth rate for each quarter. There is also a small seasonal related to the option expiration cycle. The results below are not sensitive to removing this component.

\textsuperscript{24} Estimation error in the cointegrating relationship adds further noise to \( y_t \), which works against our ability to detect significant covariates.

\textsuperscript{25} Both series are available from \url{http://www.cboe.com/micro/vix/historical.aspx}. 58
variable is 0.39.

We will discuss the economic interpretation of these responses below. Intuitively, they tell us that, under most market conditions, increases in variance and left-tail risk elicit negative quantity responses. However, the effect may be reversed when both VIX and SKEW are above their means, which can be viewed as times of high market stress.

The third column of the table adds another dimension of risk: the volatility of volatility. The motivation for this variable is the theory that a primary purpose of index options may be volatility risk transfer. We estimate this series by fitting an EGARCH model (Nelson (1991)) to daily changes in log of VIX itself. We find an independent and statistically significant positive response to this variable. High volatility of volatility again indicates conditions of high market stress, in which both tails of the return distribution expand.

Figure 2.9: Effect of Risk On Options Quantities

The rightmost column augments the options-derived measures of risk perception with two others recently introduced into the literature. Baker et al. (2013) compile the frequency of articles combining terms related to uncertainty with terms related to government policy from 10 U.S. newspapers. The authors show that their index is increasingly correlated with measures of stock market implied volatility as the forecast horizon increases. In other words, it may be seen as capturing long-term volatility as opposed to the 30-day horizon used in the construction of VIX. Manela and Moreira (2015) similarly use a machine-learning algorithm to identify uncertainty-relevant language appearing on the front pages of the Wall Street Journal.

\footnote{\cite{footnote}}

\footnote{To perform this estimation on the longest possible time series, we create a new volatility proxy using the CME data, which goes back to 1983. This series is constructed using a kernel density weighting of CME option implied volatilities, wherein the weighting on moneyness and expiration are chosen to maximize the fit to VIX in the post-1990 period. Details are available upon request.}
Table 2.6: Risk Effects in Index Option Quantities

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>-0.5561</td>
<td>-0.5586</td>
<td>-1.6351</td>
<td>-1.6143</td>
<td>-1.4452</td>
</tr>
<tr>
<td></td>
<td>(4.00)</td>
<td>(4.04)</td>
<td>(7.41)</td>
<td>(8.17)</td>
<td>(6.15)</td>
</tr>
<tr>
<td>SKEW</td>
<td>-0.3452</td>
<td>-20.5192</td>
<td>-18.9961</td>
<td>-10.3758</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.47)</td>
<td>(6.49)</td>
<td>(6.58)</td>
<td>(2.94)</td>
<td></td>
</tr>
<tr>
<td>VIX*SKEW</td>
<td>6.8515</td>
<td>6.3512</td>
<td>3.5318</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.64)</td>
<td>(6.70)</td>
<td>(2.98)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\sigma_{VIX})</td>
<td>0.3224</td>
<td>0.3849</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.12)</td>
<td>(4.91)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BBD</td>
<td>-0.3055</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.90)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MM</td>
<td>0.7652</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(4.82)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.24</td>
<td>0.25</td>
<td>0.32</td>
<td>0.36</td>
<td>0.51</td>
</tr>
<tr>
<td>(N)</td>
<td>5776</td>
<td>5776</td>
<td>5776</td>
<td>5776</td>
<td>5042</td>
</tr>
</tbody>
</table>

The table shows OLS regressions of aggregate index option quantities on volatility statistics measures of risk. The dependent variable is the log of aggregate open interest detrended as described in the text. VIX and SKEW are model-free measures of the second and third moments of the option-implied distribution of 30-day ahead index returns computed by the CBOE. \(\sigma_{VIX}\) is the daily estimated volatility of volatility. BBD is a series from Baker et al. (2013) of intensity of economic policy news stories. MM is an index of uncertainty news intensity used in Manela and Moreira (2015). All variables are in logarithms. Newey-West (1987) \(t\) statistics (shown in parentheses) are computed with one year of lags. The sample period is January 5, 1990 to December 31, 2012.

Based upon extensive analysis of drivers of variation in their index, these authors argue that the component that is not related to stock market uncertainty is strongly correlated with the probability of rare disasters.

Our regressions find independent and economically large explanatory power for both variables in explaining option quantities. The regression \(R^2\) now exceeds 50 percent. The signs of the effects are opposite, despite the similarity of construction. Intriguingly, interpreting each of the indexes as proposed by their creators, the message again seems to be of a negative response to (long-horizon) variance, with a positive response to extreme stress (disasters).

To get a closer look at quantity responses to variance and skewness, we run similar regressions for open interest of different types of options. Table 2.7 shows the dynamic responses

---

\(^{27}\)We are grateful to the authors for making this series available to us.
to VIX and SKEW of open interest for each of the 12 buckets defined in Section 3. To avoid mechanical effects, these regressions are run in differences, holding the basket breakpoints fixed across successive days.\textsuperscript{28} Open interest changes for each basket are expressed as a fraction of the trailing 3-month average level of open interest in that basket. The table shows the sum of the contemporaneous response and one-lag response coefficients.

Table 2.7: Risk Responses by Option Type

<table>
<thead>
<tr>
<th></th>
<th>low strike</th>
<th>at-the-money</th>
<th>high strike</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>calls, long-term</td>
<td>-0.1314***</td>
<td>0.0080</td>
<td>0.0852***</td>
</tr>
<tr>
<td>calls, short-term</td>
<td>-0.1683***</td>
<td>-0.0272</td>
<td>0.0409**</td>
</tr>
<tr>
<td>puts, long-term</td>
<td>-0.0489***</td>
<td>0.2112***</td>
<td>0.0944***</td>
</tr>
<tr>
<td>puts, short-term</td>
<td>0.0213</td>
<td>0.3323***</td>
<td>0.1414***</td>
</tr>
<tr>
<td>SKEW</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>calls, long-term</td>
<td>0.1060</td>
<td>0.1885**</td>
<td>-0.1536**</td>
</tr>
<tr>
<td>calls, short-term</td>
<td>0.1343</td>
<td>0.2333**</td>
<td>-0.2095***</td>
</tr>
<tr>
<td>puts, long-term</td>
<td>-0.0872</td>
<td>0.1019</td>
<td>-0.0033</td>
</tr>
<tr>
<td>puts, short-term</td>
<td>-0.0509</td>
<td>0.1357</td>
<td>-0.3374***</td>
</tr>
</tbody>
</table>

The table reports regressions of the change in open interest for options classified by type as described in the caption to Table 2.3. The independent variables are the contemporaneous change in VIX and SKEW and one daily lag of each as well as of the dependent variable. The sum of the response coefficients to VIX and SKEW are reported. One, two, and three asterisks denote rejection of the null that the coefficient sums are equal to zero at the 90%, 95% and 99% thresholds, respectively. The sample period is January 5, 1990 to December 31, 2012.

The table shows that the unconditional negative response to VIX documented above is driven by low strike price options, with high strike and at-the-money options actually responding positively. As we saw in Table 2.3, long-term, low strike puts comprise about 30 percent of all open interest. By put-call-parity, low strike calls are effectively equivalent to low strike puts with respect to crash risk. These represent an additional 7-13 percent of open interest. Chen et al. (2014) document that closing of open positions in far out-of-the-money index puts predicts (positive) stock market returns and attribute this to market makers reacting to tightening VaR constraints by shedding risky positions in general (i.e. including stocks themselves). The pattern we document is consistent with covering of crash risk positions by protection sellers in response to increased market variance. However, it is

\textsuperscript{28}Specifically, at date \( t \) we examine the change in open interest from \( t-1 \) to \( t \) for options whose strike and maturity place them in basket \( k \) at date \( t \). The regressions also include a lag of the dependent variable.
well known that VIX does not predict future stock returns. So the position covering isolated by Chen et al. (2014) is likely driven by something other than dealer responses to increases in market risk.

Low strike put positions also contract in response to increased left tail risk (although now there is a positive response in the low strike calls). Perhaps surprisingly, positions exposed to right-tail risk – high strike puts and calls – also contract on an increase in SKEW. By contrast, at-the-money positions, which have the highest gamma, expand.

Table 2.8: Risk Effects: Physical versus Risk-Neutral Uncertainty

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tbody>
<tr>
<td>E[σ²]</td>
<td>-0.3623</td>
<td>-0.161</td>
<td>-0.3724</td>
<td>-0.1882</td>
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<td>-0.1105</td>
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<tr>
<td></td>
<td>(4.50)</td>
<td>(2.75)</td>
<td>(4.08)</td>
<td>(2.39)</td>
<td>(1.96)</td>
<td>(2.25)</td>
</tr>
<tr>
<td>VRP</td>
<td>-0.1824</td>
<td>-0.0827</td>
<td>-0.1903</td>
<td>-0.0705</td>
<td>-0.0359</td>
<td>0.0658</td>
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<tr>
<td></td>
<td>(1.86)</td>
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<td>(1.94)</td>
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<td>(1.21)</td>
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<td>U(3)</td>
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<td>-1.4390</td>
<td>-0.7622</td>
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<td></td>
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<tr>
<td></td>
<td>(3.14)</td>
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<td>(3.03)</td>
<td>(4.17)</td>
<td>(5.45)</td>
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<tr>
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<td>(0.07)</td>
<td>(0.55)</td>
<td>(1.02)</td>
<td>(1.76)</td>
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<td></td>
</tr>
<tr>
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<td>0.29</td>
<td>0.46</td>
<td>0.58</td>
<td>0.49</td>
</tr>
<tr>
<td>N</td>
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</tbody>
</table>

The table shows OLS regressions of aggregate index option quantities on measures of physical and risk-neutral uncertainty, and risk-aversion proxies. E[σ²] is the 30-day-ahead forecast variance from an EGARCH model of market returns. VRP is the difference between the VIX index (squared) and this forecast. U(3) is index of mac-roeconomic uncertainty at the 3-month horizon created by Jurado et al. (2015). cns.cnf is the University of Michigan index of consumer confidence. r₁Q is the trailing three-month return on the market index. Column (6) repeats the specification in (5) with open interest in out-of-the-money puts as the dependent variable. All the risk variables are in logarithms. Newey-West (1987) t statistics (shown in parentheses) are computed with one year of lags. The sample period is January 5, 1990 to December 31, 2012.

Risk measures derived from options prices reflect both risk and risk aversion (marginal utility) in investor perception of future states. That is, they reflect the “risk neutral” distribution of stock returns, rather than the “physical” or “true” distribution. This raises the question of whether option quantity responses in Table 2.6 are reflecting the endogenous
risk aversion component or the exogenous risk component. To get at this issue, we do three things. First, we decompose VIX into a statistical forecast of true market return variance and a residual that can be interpreted as the variance risk premium (VRP). Second, we include a gauge of exogenous economic risk not derived from options prices or stock returns. Third, we include proxies for investor sentiment (or risk aversion).

For the variance return forecasts, we fit an EGARCH model to daily futures returns since 1983 that includes asymmetry effects and leptokurtosis (via $t$ distributed innovations). The model delivers one-day-ahead expected return variances every day. We iterate the forecasts to 30-day horizon for comparability with VIX.

The exogenous risk measure, taken from Jurado et al. (2015), is a formal estimate of the conditional second moment of a broad cross-section of macroeconomic time-series at the monthly level. The authors estimate prediction equations for 132 variables that explicitly allow for time-varying first and second moments. They then average the forecast standard deviations to different time horizons. We employ their three month measure $\bar{U}_y(3)$.

For risk aversion, we employ the University of Michigan consumer confidence index, $cns.cnf$, as well as the lagged quarterly return on the S&P 500 index itself, $r_{1Q}^m$ to proxy for possible extrapolative expectations.

Table 2.8 shows regression results with these controls. The first column establishes that the negative response of $OI$ to VIX is driven by the true variance component. There is also some evidence of a negative response to the variance risk premium, but the statistical significance is not robust across specifications. Column (2) confirms this conclusion by showing that the negative response to the Jurado et al. (2015) measure of “fundamental” risk is even stronger than the response to forecasted stock market volatility.

Moreover, the risk aversion proxies in (3) - (4) do not appreciably change the uncertainty effect. Interestingly, when both these variables and $\bar{U}_y(3)$ are included (in (4)), we see a substantially larger coefficient on exogenous risk and a significant negative response to the consumer confidence measure. If this measure is indeed picking up investor risk aversion, and if risk aversion was partially responsible for the negative variance response, then one would have expected a positive response to $cns.cnf$ (since lower values indicate pessimism).

Column (5) in the table includes the BBD measure that we interpreted above as potentially capturing longer horizon variance, but which is a measure of investor concerns and thus also

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29The forecasts use information in 279 time series: the macro series plus 147 financial predictors. The uncertainty measures are taken from http://www.econ.nyu.edu/user/ludvigsons/jlndata.zip.

30For brevity, the table focuses on second-moment proxies and omits the ones from Table 2.8 that we interpreted as higher measures of tail risk.

31The finding that there is no significant response of index options positions to market returns is robust to the return horizon: lagged one-week and one-month returns also have no significant effects.
reflects risk and risk aversion. This variable again enters significantly negatively and more strongly than in Table 2.6. It also strengthens the negative response to consumer sentiment, suggesting that the BBD response is due to the fundamental, exogenous component of risk in this index.

Finally, since Table 2.3 shows that out-of-the-money puts comprise, on average, almost half of open interest, we repeat specification (5) using only these options as the dependent variable. Our specifications have less overall explanatory power for the low-strike puts. The responses to the uncertainty variables are somewhat weaker, but still statistically significant.

Table 2.9: Risk Effects: Uncertainty versus Disagreement

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BOS</td>
<td>0.4863</td>
<td>1.526</td>
<td>1.3196</td>
<td>0.8377</td>
<td>0.5162</td>
</tr>
<tr>
<td>SPF</td>
<td>-0.1417</td>
<td>0.1163</td>
<td>0.0442</td>
<td>0.0321</td>
<td>-0.1437</td>
</tr>
<tr>
<td>(\bar{U}\y(3))</td>
<td>-2.5481</td>
<td>-3.1221</td>
<td>-2.1458</td>
<td>-1.0752</td>
<td></td>
</tr>
<tr>
<td>CNS_CNF</td>
<td>-0.0099</td>
<td>-0.0173</td>
<td>-0.0187</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BBD</td>
<td>-0.4249</td>
<td>-0.4149</td>
<td>0.50</td>
<td>0.59</td>
<td>0.49</td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.03</td>
<td>0.42</td>
<td>0.50</td>
<td>0.59</td>
<td>0.49</td>
</tr>
<tr>
<td>(N)</td>
<td>5548</td>
<td>5548</td>
<td>5548</td>
<td>5548</td>
<td>5548</td>
</tr>
</tbody>
</table>

The table shows OLS regressions of aggregate index option quantities on measures of survey dispersion and other controls. BOS and SPF are constructed from, respectively, the Business Outlook Survey and the Survey of Professional Forecasters. Both surveys are compiled by the Federal Reserve Bank of Philadelphia. Column (5) repeats the specification in (4) with open interest in out-of-the-money puts as the dependent variable. Newey-West (1987) \(t\) statistics (shown in parentheses) are computed with one year of lags. The sample period is January 5, 1990 to December 31, 2012.

Another important distinction in the measurement of risk is between uncertainty and disagreement. It seems plausible that differences of opinion between market participants are correlated with fundamental risk. This can be investigated using measures of survey dispersion. As discussed in the introduction, there is a strongly grounded prediction for a

---

32When using out-of-the-money puts, the regressions also control for contemporaneous market returns because of the mechanical effect: a fall in the market automatically leads to fewer out-of-the-money strike prices, etc.
positive relationship between measures of heterogeneity – like differences of opinions – and quantities of options positions. We have, however, documented the opposite relationship to volatility measures. This implies that, controlling for uncertainty, the regressions can isolate the belief differences as components of survey dispersion.

We have two dispersion measures. The first (called BOS) is from Bachmann et al. (2013), and is constructed from the dispersion in responses to the Business Outlook Survey conducted monthly by the Philadelphia Federal Reserve.\(^{33}\) This is a regional survey of executives of manufacturing firms and concerns their operational climate. In contrast, the Survey of Professional Forecasters (SPF), also compiled by the Philadelphia Federal Reserve, is a quarterly assessment of the national economic outlook as gauged by economists. We employ the interquartile range of forecasts for real GDP growth in the current quarter.\(^{34}\)

Table 2.9 shows that there is no evidence that these dispersion measures relate to options positions on their own (first column) but that, controlling for macroeconomic uncertainty (second column) the predicted positive role for disagreement does emerge, at least using the BOS survey.\(^{35}\) The conclusion is reinforced by inclusion of the indexes for consumer confidence and policy uncertainty (in (3)-(4)). Specification (5) uses only the out-of-the-money put open interest, which yields less positive dispersion responses, comparable to those in (1).

While the incremental explanatory power for index option positions of the BOS measure is small in our regressions, it is perhaps remarkable to find an association at all given that the topic of the survey (local manufacturing outlook) is several steps removed from the direct concerns of the index options markets.

Summarizing the results in this section, we highlight the following conclusions.

1. The most significant determinant of fluctuations in $OI$ is a negative response to risk, which is not driven by the risk-aversion component in measures of investor sentiment, nor by differences of opinion. For example, regressions including only $E[\sigma^2]$ and $\bar{U}_y(3)$ achieve an $R^2$ of 40 percent.

2. Increases in belief dispersion and deterioration of investor sentiment induce significant positive responses of $OI$. Even with limited proxies for these, explanatory power

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\(^{33}\)This series and the BBD measure are from [http://www.aeaweb.org/articles.php?doi=10.1257/mac.5.2.217](http://www.aeaweb.org/articles.php?doi=10.1257/mac.5.2.217).

\(^{34}\)These measures only capture disagreement about the first moment of economic activity (i.e. expected growth), and do not speak to differences in beliefs about higher moments.

\(^{35}\)Our findings here accord with those of Buraschi and Jiltsov (2006) who build a model of options trade driven by differences of belief about the economic state and calibrate it using a survey-based measure of disagreement. Overidentifying tests fail to reject the model’s restrictions on open interest changes for a cross-section of S&P 500 options during 1986-1996. Regression evidence is moderately supportive of a positive association between option volume levels and belief differences.
approaches 60%. (e.g. specification (4) in Table 2.9).

3. There is also evidence of a positive quantity response to some measures of tail risk (the VIX-SKEW interaction, volatility of volatility, and MM index). Unreported regressions combining these with the variables above yields an $R^2$ over 70%.

The negative risk response is consistent with the model of Chen et al. (2014) in which one class of agents (e.g., dealers) have tolerance for unspanned crash risk that is higher than that of another class (e.g., investors) in normal times, but which diminishes rapidly in the face of rising risk, possibly due to binding VaR constraints (that do not apply to the investors). The contrasting positive responses we document present a more complex challenge to theorists. One possibility is that these measures are all, to some extent, picking up subjective measures of investor sentiment or marginal utility, to which dealers are less susceptible.

Whatever the correct interpretation, empirically we have succeeded to a significant degree in describing the factors driving index options positions. As Figure 2.10 illustrates, the fitted specification (model (4) of Table 2.8 is shown) tracks the historical data series closely for over 20 years.

2.6 Conclusion

A enormous and still-growing body of research studies stock index option prices. This literature recognizes the unique ability of this class of derivatives to identify investor preferences and risk assessment. We contribute to this research by presenting the first comprehensive look at quantities of these options. A complete understanding of the role that these options play in the economy should aim to explain both the price and quantity dimensions. Our work thus fills an important gap in the empirical options literature.

Measured in terms of monetary value or gross volatility exposure, the index options market is small. But it is large in terms induced of exposure to jumps. Out-of-the-money puts constitute the predominant position type, suggesting that the primary function of this market is the transfer of unspanned crash risk.

Guided by theories of derivative usage, we seek to explain the time-variation in options exposures by variables potentially capturing frictions, types of heterogeneity, and risks.

The stochastic trend in options usage is well-described by exogenous equity market activity. We interpret the explanatory power of stock market turnover as proxying for heterogeneity (and possibly frictions). Direct evidence on the nature of this heterogeneity is still lacking. It does not appear to be linked to the participation shares, or retail (household) investors or that of mutual funds, pensions, or banks and brokers.
We also do not find evidence linking options quantities to proxies for trading costs, information technology, or interest rates. While the available proxies are not ideal, this finding speaks to a widely-held view that options offer cost advantages to some investors, and that this drives demand.

Finally, Using a rich collection of uncertainty proxies, we distinguish distinct responses to exogenous macroeconomic risk, risk aversion, differences of opinion, and disaster risk. Together these can explain most of the variation in detrended open interest. The single most important relationship is a strong negative response to increases in variance. This is consistent with a negative supply effect driven by sellers of crash risk.

Overall, these findings lay the groundwork for further development and testing of theoretical models of multi-agent economies.
CHAPTER 3

EXPLORING THE MIDAS TOUCH: INVESTMENT BANK CONNECTIONS AND MUTUAL FUND RETURNS

3.1 Introduction

Understanding the sources of gains in the delegated asset management industry is both of academic interest and practical importance. According to French (2008), individual investors increasingly delegate their investing decisions to professional investors. Does the performance of the professional investing industry, especially mutual funds – one of the biggest industry players – at least partly justify the public trust? Academic literature generally takes a more skeptical view of mutual fund performance in general. Empirical regularities indicate that the actively managed fund does not outperform passive investment strategies on average, net of fees and after controlling for differences in systematic risk exposure. However, a small subset of funds persistently outperforms the rest. One question naturally arises: what drives the superior performance of a small group in the mutual fund industry?

One strand of promising answers lies with private information. Starting from Grossman and Stiglitz (1976), academic literature reaches a consensus that information acquisitions by a certain group of investors affects asset price movements. If certain types of investors have incentives to costly acquire certain information relevant to asset price, yet clandestine to investors in general, then we must observe them earning a return from asset price moving in the corresponding direction in the future. Otherwise, those investors will not have incentives to acquire information which is costly. Correspondingly, Kacperczyk and Seru (2007) find that the sensitivity of changes in mutual fund portfolio allocations to the release of public information, which is freely accessible to all investors, decreases with fund managers’ skills and fund performance. In general, the theoretical and empirical evidence indicate that access to relevant private information is at least partly responsible for superior alphas generated by skillful mutual funds. Although the information acquisition channel is theoretically promising, empirical evidence for fund managers’ information acquisition behavior is scant, since observing their day-to-day activities is impossible. Even identifying the source of private information possessed by fund managers is empirically a daunting task.

This paper fills the gap by examining the fund managers’ exposure to one of the informa-
tion nexus of capital markets, i.e., investment banks, and their impact on fund managers’ portfolio allocation decisions, trading decisions ahead of value-relevant event realizations, and portfolio performance. On the one hand, it is well-documented that investment banks glean superior information about their clients through IPO marketing, M&A advising, etc. The information possessed by investment banks is so crucial that it affects their clients’ decisions in choosing investment banks with which to do business. Specifically, the information accumulation by investment banks forces corporate America to retain a long-term relationship with one investment bank, and avoid using the same investment bank as their competitors (Asker and Ljungqvist, 2010). On the other hand, recent literature has documented that information often disseminates through social ties among economic agents. Those social ties are built over time through a common alma mater, common work experiences, and even shared avocational activities (e.g., Cohen et al. (2010); Engelberg et al. (2012)). Built on these two strands of literature, we conjecture that mutual fund managers’ previous work experience in investment banks facilitates access to covert information regarding clientele firms of their previous employers. As a result, the trading decisions made by “connected” managers regarding those clientele firms’ stocks should, on average, generate positive abnormal returns, compared with trading decisions made regarding other stocks in the same portfolio. Investment banks have a particularly good guess about the outcome of some corporate events they are directly involved with, such as M&A deals. Therefore, trading decisions made by those connected managers, ahead of those corporate events, should predict the eventual outcome of those events.

These hypotheses are echoed in our findings. Specifically, utilizing the BrokerCheck and Investment Adviser Public Disclosure (IAPD) databases from FINRA and SEC, respectively, we collect work experience information in investment banks for a group of 500 randomly selected mutual funds included in the CRSP survival-bias free mutual funds, and fund managers of each fund, as archived by MorningStar Global Fund Managers Database. First of all, investment banks constitute a significant part of the career path of average mutual fund managers. Out of 499 mutual funds in our sample, about half of their managers worked in investment banks before joining the asset management industry. Moreover, a simple trading strategy that follows the fund managers’ quarterly reported portfolio allocations on stocks from their former employers’ clients generates a meaningful 88 basis points monthly abnormal return from the Fama-French four factor model, while mimicking the same manager’s portfolio allocations on ”nonconnected” stocks’ general alphas from the same factor model indistinguishable from zero. The difference in abnormal returns between the two portfolio allocations is 77 basis points per month, which is both economically and statistically significant.
Having documented superior abnormal returns generated by fund managers’ trading decisions regarding stocks from their former employers’ clients, we proceed with a change-in-change type of robust check. Specifically, we find that the abnormal return disappears once the underlying firm in question switched to a new investment bank that the fund manager did not work with before the current job. Lastly, using Lehman Brothers demise in 2008 as an exogenous shock to the information tie for fund managers previously employed by Lehman, we again find that the positive abnormal return from trading decisions made on connected stocks in the Lehman-connected managers’ portfolios disappears after Lehman’s bankruptcy.

The last part of this analysis documents one possible channel through which fund managers get value-relevant information from their former employers. Investment banks play a significant role in most of the M&A deals (e.g., Derrien and Dessaint (2014)). It is also well-documented that takeover targets earn significant positive returns after the M&A announcements. Correspondingly, we find that the mutual fund managers’ holdings percentage of a connected stock has predictive power of the firm becoming an M&A target in the near future. The significant predictability is not present in M&A deals involving target firms independent of fund managers according to our professional tie. Overall, we document that one important channel through which a certain group of mutual funds generates positive and persistent alphas is their acquisition of private information using their social relations with investment banks.

**Related Literature** Our paper contributes broadly to two strands of literature. First is the drivers of mutual fund alphas. Empirical literature documents that actively managed mutual funds do not outperform passive investment strategies, after taking fees and systematic risk-taking into consideration. However, a small group of mutual funds consistently outperforms the rest of the industry. Moreover, the stock pick ability of those best performing mutual funds are empirically more compelling compared with market-timing ability (e.g., Kacperczyk et al. (2014)). Our paper complements this strand of literature by documenting that one potential channel, through which mutual fund managers glean value-relevant private information and make investment decisions accordingly, is using professional connections to their previous investment bank employers and investing stocks of those investment banks clients. Since the investment banking business features oligopoly, with a handful of investment banks dominating various types of the investment banking business, our findings with regard to information leakage through investment banking employment relationships shed light on a broad sector of public traded stocks.

Moreover, our paper also contributes to the social network in finance literature. Recent
empirical works show that social networks facilitate information transmission in various sectors of financial markets. For example, Cohen et al. (2008) show that mutual fund managers who share common educational and vocational ties with corporate board members generate positive abnormal returns for the firms boarded by those directors. Cohen et al. (2010) similarly find that sell-side analysts connected with corporate officers through common alma maters make more profitable stock recommendations for the firms employing those connected officers. In corporate finance literature, Engelberg et al. (2012) document a lower cost of bank loans when the lender and borrower share similar education and work experience. The borrowers’ stock return and credit rating improve following such connected loan deals. Our paper contributes to the literature by documenting a new type of social connection between fund managers, and the stocks they invest in, through business operations and employment practices of the investment banking industry. As investment banks play crucial roles in most capital market transactions, either facilitating the information transmission, or reducing the adverse selections, our findings could extend to other contexts where investment banking is central.

The remainder of the paper is organized as follows: Section 2 presents the empirical methodology and proxies for fund-bank and firm-bank connections; Section 3 presents the empirical results; Section 4 offers concluding remarks.

3.2 Empirical Methodology

In this section, we construct the empirical proxy of fund-bank and firm-bank connections, and explain the details of several data resources.

3.2.1 Fund-Bank Connection

In this paper, we use mutual fund manager’s past investment bank work experience as a proxy for the fund-bank connection. Since there is no available database for this, we hand collect the work experience information in investment banks for a group of 500 randomly selected mutual funds included in the CRSP survival-bias free mutual funds, and fund managers of each fund, as archived by MorningStar Global Fund Managers Database. We start from the CRSP mutual fund holdings data, where we get all the mutual fund managers’ holdings and their full names. We merge CRSP and MorningStar data sets by managers’ last name and then search managers’ names in Investment Adviser Public Disclosure (IAPD) from SEC and BrokerCheck from FINRA. IAPD provides information about current and certain
former Investment Adviser Representatives, Investment Adviser Firms registered with the SEC and/or state securities regulators, and Exempt Reporting Advisers that file reports with the SEC and/or state securities regulators. BrokerCheck provides information about current and former FINRA-registered brokers and brokerage firms.

We match 370 mutual fund managers from the four data sources. We then narrow down the mutual funds with a single manager. We also exclude all index funds and bond funds in the sample. In our sample, a mutual fund manager may have several past work experiences with different investment banks. We only consider his/her latest work experience. In the end, our final data set covers 499 equity mutual funds and 199 ”connected” mutual fund managers.

3.2.2 Firm-Bank Connection

To proxy the firm-bank connection, we follow the literature standard and use the SDC data. We use the firm’s past 5 years’ M&A advising and issuance underwriting business with an investment bank as a proxy for the firm-bank connection. We focus on the top 100 investment banks. The advising and underwriting business includes all deals related to M&A, IPO, SEO, preferred stock, convertible bond, nonconvertible bond, private equity and private debt. There are three possible cases regarding the firm-bank connection: ”NonConnected”, ”UniConnected” and ”MultiConnected”. For each firm, at each quarter, we look at the past five-year window. If there is no deal at all, then firm is ”NonConnected”. If all deals are advised from the same investment bank, then firm is ”UniConnected” to this bank. If deals are advised from different banks, the firm is ”MultiConnected”. In this paper, we only consider the ”UniConnected” case as the information tie between bank and firm. Thus, when we mention ”connected”, we really mean uniquely connected.

3.3 Results

In this section, we develop hypotheses and test them empirically. We first present the evidence of mutual fund managers’ superior performance on stocks which are connected to the investment bank for which they used to work. Then we examine two events that break the information tie: 1) firm switching investment bank; and 2) collapse of Lehman Brothers. Mutual fund managers’ stock picking skills disappear after the network breaks. Finally, we present evidence of M&A takeover information leakage in this network. All empirical evidence shows that social networks facilitate information transmission in financial markets.
3.3.1 Hypothesis I: Superior Performance

**Hypothesis I**  *If there is information flow in the network, the fund manager will show stock picking skills on the connected stocks. Connected stocks will outperform the non-connected stocks.*

To test this hypothesis, we construct a zero-investment long-short portfolio strategy. At the end of each quarter, mutual fund managers report their portfolio holdings. Each stock in the manager’s portfolio holdings is classified as ”connected” or ”non-connected” depending on whether the firm is uniquely connected to the investment bank for which the manager formerly worked. Then we form value-weighted portfolios. A zero-investment portfolio is also formed by taking a long position of connected stocks and a short position of non-connected stocks. We regress the portfolio returns on standard Fama-French 3 factors and Fama-French 3 plus momentum 4 factors.

<table>
<thead>
<tr>
<th>Panel A: 1-mo Abnormal Return on the Reporting Month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connected</td>
</tr>
<tr>
<td>FF3</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>FF3+UMD</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: 3-mo Abnormal Return after the Reporting Month</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connected</td>
</tr>
<tr>
<td>FF3</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>FF3+UMD</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

The abnormal returns are reported in Table 3.1. Panel A presents the results from trading strategies of investing for only 1 month on the reporting month. Panel B presents results from trading strategies of investing for 3 months after the reporting month. All portfolios are re-balanced every quarter, since we only have a quarterly snapshot of managers’ holdings. The zero-investment portfolio earns a significant abnormal return of 54 to 77 bps per month. The abnormal returns are mainly driven by the long side of the trading strategy. The evidence supports our prior hypothesis. Managers show stock picking skills on the connected stocks.

We take a further look at the superior performance of the connected stock portfolio. Within this group, we re-examine the firm-bank connection, depending on how long ago
the firm-bank connection was built. We shorten the time window to one year. Within the one year window, if there is at least one advising or underwriting deal, the firm is classified as short-term connected (“ST-Connected”); otherwise it is classified as non-short-term connected (“Non-ST-Connected”). Table 3.2 shows abnormal return regression results using the 4 factors model. The "ST-Connected" portfolio earns significant positive abnormal returns of 72 bps per month. However, the "Non-ST-Connected" portfolio’s alpha is not statistically significant, though positive. We see the positive performance is mainly driven by the short-term connected group. This is consistent with the finding that investment banks glean superior information about their clients through various advising and underwriting businesses.

Table 3.2: Short Term Connected

<table>
<thead>
<tr>
<th>3-mo Abnormal Return after the Reporting Month</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Connected</td>
<td>ST-Connected</td>
</tr>
<tr>
<td>FF3+UMD</td>
<td>0.0056**</td>
</tr>
<tr>
<td></td>
<td>(2.06)</td>
</tr>
</tbody>
</table>

3.3.2 Hypothesis II: Switching Investment Banks

**Hypothesis II** *When the firm-bank link breaks, the manager’s stock picking skills will disappear.*

Firms may not always maintain a business relationship with one particular investment bank, for various reasons. In our data sample, we do see firms switching investment banks. This provides a very good set-up to test our main hypothesis of information flow within a social network in a diff-in-diff manner. When firms switch to a new investment bank, the old bank will not have the most updated information, thus managers connected to the old bank will not show superior stock picking skills after the break of this information tie.

Table 3.3 presents the portfolio returns regression results using the 4 factors model. Consistent with our prior hypothesis, mutual fund managers show stock picking skills before the firm-bank link breaks. Connected stocks portfolios earn significant abnormal returns of 56 to 86 bps per month before firms switch investment banks. However, the superior performance disappears right after the firm switches its investment bank.
Table 3.3: Firm Switching Investment Bank

<table>
<thead>
<tr>
<th></th>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td>FF3+UMD 1-mo Abnormal</td>
<td>0.0086**</td>
<td>-0.0014</td>
</tr>
<tr>
<td></td>
<td>(2.17)</td>
<td>(-0.19)</td>
</tr>
<tr>
<td>FF3+UMD 3-mo Abnormal</td>
<td>0.0056**</td>
<td>-0.0020</td>
</tr>
<tr>
<td></td>
<td>(2.06)</td>
<td>(-0.49)</td>
</tr>
</tbody>
</table>

3.3.3 Hypothesis III: Collapse of Lehman Brothers

**Hypothesis III**  
*When the fund-bank link breaks, the manager’s stock picking skills will disappear.*

In this part, we explore another connection breaking event – the collapse of Lehman Brothers in 2008. After Lehman collapsed, Lehman-connected mutual fund managers lost their information tie with Lehman-connected firms. Thus we conjecture that Lehman-connected mutual fund managers’ stock picking skills will disappear after the fund-bank connection breaks.

Results from Table 3.4 are consistent with our prior conjecture. Lehman-connected managers show superior positive performance before 2008. When Lehman Brothers collapsed, the Fund-Bank connection broke, and Lehman-connected managers’ stock picking skills on Lehman-connected stocks disappeared.

3.3.4 Takeover News

Investment banks play a significant role in most of the M&A deals. It is well-documented that takeover targets earn significant positive returns after the M&A announcement. In this section, we test whether mutual fund managers take advantage of private information regarding M&A takeover deals. To test this hypothesis, we perform a logit regression specified in equation (3.1). The left-hand variable is a dummy variable showing whether a firm becomes an M&A target in the following quarter. The key right-hand variable is the percentage of stock holdings in a manager’s portfolio. We conjecture that if a manager has private information regarding an M&A takeover deal, he/she will take a significant long position of the target firm before the announcement. The logit regression results are presented in Table 3.5.
Table 3.4: Collapse of Lehman Brothers

<table>
<thead>
<tr>
<th>1-mo Abnormal Return on the Reporting Month</th>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connected</td>
<td>0.0238**</td>
<td>-0.0109</td>
</tr>
<tr>
<td></td>
<td>(2.48)</td>
<td>(0.20)</td>
</tr>
<tr>
<td>Non-Connected</td>
<td>0.0030</td>
<td>0.0031</td>
</tr>
<tr>
<td></td>
<td>(1.23)</td>
<td>(0.55)</td>
</tr>
<tr>
<td>Long-Short</td>
<td>0.0185*</td>
<td>-0.0161</td>
</tr>
<tr>
<td></td>
<td>(2.03)</td>
<td>(0.29)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>3-mo Abnormal Return after the Reporting Month</th>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Connected</td>
<td>0.0110**</td>
<td>0.0182</td>
</tr>
<tr>
<td>(2.26)</td>
<td>(1.48)</td>
<td></td>
</tr>
<tr>
<td>Non-Connected</td>
<td>-0.0002</td>
<td>-0.0011</td>
</tr>
<tr>
<td>(-0.09)</td>
<td>(-0.55)</td>
<td></td>
</tr>
<tr>
<td>Long-Short</td>
<td>0.0089*</td>
<td>0.0202</td>
</tr>
<tr>
<td>(1.69)</td>
<td>(1.54)</td>
<td></td>
</tr>
</tbody>
</table>

The $PctHoldingInPortfolio$ variable has no predictive power of the firm becoming an M&A target in the non-connected group. But it has predictive power in the connected group.

$$Logit(0|1Takeover)_{it} = \beta PctHoldingInPortfolio_{i,t-1} + \gamma_i Controls_{i,t-1} + \epsilon_t$$  (3.1)

3.4 Conclusion

This paper examines the mutual fund managers’ exposure to one of the information nexus of capital markets, i.e., investment banks, and their impact on fund managers’ portfolio allocation decisions, trading decisions ahead of value-relevant event realizations, and portfolio performance. On the one hand, it is well-documented that investment banks glean superior client information through IPO marketing, M&A advising, etc. On the other hand, information often disseminates through social networks among economic agents. Built on these two strands of literature, we investigate whether mutual fund managers’ previous work experience in investment banks facilitates their access to covert information regarding clientele firms of their previous employers.
To use social networks to identify information transfer in security markets, we focus on connections between mutual fund managers and investment banks via managers’ past work experience. We find mutual fund managers show significant stock picking skills on firms which are the long-term clients of the investment banks for which the managers have formerly worked. Managers perform significantly better on connected holdings relative to non-connected holdings. A replicating portfolio of connected stocks outperforms a replicating portfolio of non-connected stocks by approximately 7.4% per annum. We also compare the stock performance before and after two network-break events (firm switching investment banks and Lehman’s collapse) and find that managers’ stock picking skills disappear when connections break.

We also document one possible channel through which fund managers obtain value-relevant information from their former employers – M&A takeover news. We find that the mutual fund managers’ holdings percentage of a connected stock have a predictive power of the firm’s becoming an M&A target in the near future.

To sum up, social networks facilitate information transmission in financial markets. All empirical results are consistent with mutual fund managers gaining an informational advantage through social networks.
APPENDIX A

INDEX OPTIONS

A.1. Contract Description

This appendix provides details on the three classes of options that the study amalgamates.

CBOE S&P 500 Index (SPX) Options.

The Chicago Board Options Exchange (CBOE) began trading options based on S&P 500 index with the ticker symbol SPX in 1983. The SPX options are European style, and are cash-settled. The SPX options have a large notional size with a multiplier of 100 of the underlying index value. The CBOE has introduced numerous variants of its basic products over the years, including those with smaller denomination, end-of-quarter and end-of-week expirations, longer term (LEAPS), and closing-price settlement.\(^1\) The most liquid versions have consistently been the standard third-friday expirations on the March, June, September, December cycle augmented with the nearest two non-cycle monthly expirations. The CBOE options were exclusively pit traded until 2012 when trading in a parallel version was launched on the CBOE’s electronic exchange, known as C2.

Our data on CBOE options comes from two sources: the CBOE itself and OptionMetrics. The latter is a commercially available database going back to 1996. The CBOE itself has stored data from 1990 onward, which we acquired. Our data includes most of the minor variants listed above, as well as the flagship liquid product. The data include closing price, traded volume, and open interest for every available strike-expiration pair of puts and calls.

CME S&P 500 Futures Options.

The Chicago Mercantile Exchange (CME) began trading futures contracts referencing the S&P 500 in 1982, and introduced options on them in 1983. The underlying for each

\(^1\) Currently the standard products are settled by an average of opening prices of the underlying index stocks on expiration day. Closing-based settlement procedures were used when the options were first introduced.
option is one cash-settled futures contract; the original futures contract unit size was 500 times the index value. This was lowered to 250 in 1997. The options are American style.\footnote{Note that these options are not cash-settled: exercise results in a long or short position in the futures contract.} The futures contracts have the same quarterly, third-friday settlement calendar as the main CBOE products. The CME options may have expiration date the same as, or prior to, the future settlement. As with the CBOE, the most liquid products are the nearest few months (with standard third-friday expiration). Also like the CBOE, the CME has experimented with variants like end-of-week and end-of-month expirations with limited investor interest.

In contrast, an extremely successful variation has been the introduction of smaller denomination contracts. The CME began trading so-called “e-mini” S&P 500 futures in 1997 with a contract size of 50 times the underlying index value. In 1997, the CME listed options based on the e-mini contract, again with one option on one futures contract. In every respect other than denomination, the original (“big”) contract and the e-mini are the same: the options are American and the primary expiration dates are the same cycle. The trading mechanisms for the big and little contracts are different, however. Both futures and options on the former are primarily pit-traded, while e-mini futures and options are traded on Globex, the CME’s electronic limit order book.\footnote{The big contracts are also eligible for trade on Globex.}

Our data on futures options was purchased from the CME and goes back to contract inception in 1983. We have the same basic end-of-day statistics as for the CBOE. Coverage includes the minor contract variants, as well as the main big and e-mini options.

**Options on SPDR ETFs (SPY).**

Introduced in 1993, State Street’s Standard & Poor’s Depositary Receipts (SPDR – ticker symbol SPY) has become an extremely liquid exchange-traded fund (ETF) that is designed to closely track the S&P 500 stock market index. In 2005, the CBOE introduced options based on SPDRs. SPDRs are traded like common stock and the SPDR options have the same features as standard listed U.S. stock options: American-style exercise and physical settlement (not cash). Each SPDR options contract is on 100 units of the underlying ETF. However, the denomination of the ETF is 1/10th of the value of the S&P 500 index itself. Thus, effectively, one option on SPY references 10 index-equivalent units.

Our data on SPY options comes from OptionMetrics, which consolidates data across
multiple option exchanges.

A.2. Efficient Computation of American Option Exposures

This appendix describes the computational method used to handle the large number of American-style options on futures traded on the Chicago Mercantile Exchange. Our study requires us to aggregate the volatility exposures (“vegas”) across all options with any open interest on a given day. This, in turn, requires an “implied volatility” for each such option. Because the options are American and early exercise is sometimes optimal, closed-form solutions are not available. Numerical methods are required for two separate steps. First, a calibration step is required to deduce an implied volatility for each option. Second, the volatility sensitivity of the resulting valuation is computed. We need to do this for approximately four million option observations with nonzero open interest.

Our approach utilizes binomial trees as the basic valuation model. While trees can be made quite fast, the primary numerical challenge to a brute-force approach is in the implied volatility step, which would require an inefficient search over the space of trees.

To deal with this, we construct highly accurate, multidimensional look-up tables (LUTs). We precompute option values on a four-dimensional grid of expiration, interest rate, moneyness, and volatility. The two steps described above can then be performed through a combination of implicit and explicit interpolation within these tables, as we describe below.

For each node on the grid we evaluate call and put prices on a third-moment tree as per Tian (1993), with analytical smoothing (via Black’s formula) in the last step as suggested by Broadie and Detemple (1996). This procedure has among the best convergence properties of the methods studied by Joshi (2007).

**Implied volatility.** Given an option price, the first step is to do an implicit interpolation in our LUT to deduce the volatility which would yield that price. That is, given the time to expiration, interest rate,$^4$ and moneyness, we linearly interpolate to obtain the option values, $\hat{o}(\sigma_i)$, at each node on our volatility grid, $\{\sigma_i\}$. The volatility grid values are then treated as a function, and its value is interpolated at the observed price of the option over the grid defined by $\hat{o}$, to obtain the implied value $\hat{\sigma}$.

The procedure fails when the option price is low enough that it is in (or below) the early exercise region, where the volatility surface is not invertible. In this case, we can assign the option an implied volatility of zero without loss of accuracy because

$^4$We use the 30 day eurodollar rate from the Federal Reserves H15 survey as the riskless rate in pricing calculations.
the ultimate object of interest is the volatility sensitivity of the option, which must necessarily be zero for such an option. (These zero implied volatility values are not themselves used for anything else).

**Sensitivity.** Given the implied $\hat{\sigma}$, we obtain the volatility sensitivity via numerically differencing the values in our LUT along the volatility dimension, and then explicitly interpolating the differenced LUT at the observation’s expiration, interest rate, moneyness, and implied volatility. Our grid step size was chosen with the specific criterion of achieving acceptable accuracy of these first differences.

This step is quite efficient since 4-dimensional linear interpolation can be handled by vectorized MATLAB routine `interpn`. A single call to this routine suffices to handle all the put data; a second processes all the calls.

### A.3. Nonstationary Regressions

The inferences in the tables in Table 5 are all made under the null hypothesis that the estimated trend from the previous section correctly removes the nonstationarity from $OI$. However, it is well known that stock market turnover (which drives the fitted trend) is positively correlated with volatility. Therefore it is worth asking whether inference about the trend is affected by the presence of uncertainty variables, and vice versa. As a robustness check, we therefore run the regressions on the raw (not detrended) $OI$ series, with $TO$ on the right-hand side.

One needs to be careful econometrically with estimating such specifications, since it requires inference about the joint effects of stationary and nonstationary variables. Ordinary least squares (OLS) is not appropriate for such inference due to the spurious regression problem. However the consistency of OLS under the null of cointegration has been shown by Park and Phillips (1988,1989) who also derive the nonstandard asymptotic theory. Here we adopt the null hypothesis of a correctly specified cointegrating relationship (as per the FIML results) and we report finite-sample standard errors computed via simulation under this null.\(^5\) This specification includes no seasonal growth term. The results, shown in Table A.1 indicate that there little evidence of misestimation of the turnover coefficient due to the omission of risk variables. The risk responses themselves are somewhat attenuated in this specification, but remain economically large.

\(^5\)Specifically the simulation assumes that the nonstationary independent variables, differenced, together with the stationary independent variables follow a stationary AR(1) process, which is independent from the cointegrating residuals, which are also an AR(1) process.
Table A.1: Nonstationary Open Interest Regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>-0.3942</td>
<td>-0.9827</td>
<td>-0.9305</td>
<td>-0.9380</td>
</tr>
<tr>
<td></td>
<td>(3.15)</td>
<td>(5.21)</td>
<td>(4.74)</td>
<td>(4.82)</td>
</tr>
<tr>
<td>SKEW</td>
<td>-9.1617</td>
<td>-8.3063</td>
<td>-8.3863</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.20)</td>
<td>(2.88)</td>
<td>(2.96)</td>
<td></td>
</tr>
<tr>
<td>VIX*SKEW</td>
<td>3.4607</td>
<td>3.1707</td>
<td>3.2227</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.59)</td>
<td>(3.27)</td>
<td>(3.30)</td>
<td></td>
</tr>
<tr>
<td>$\sigma_{VIX}$</td>
<td>0.2379</td>
<td>0.1999</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(3.30)</td>
<td>(2.89)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$FDISP$</td>
<td>0.8105</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.40)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BBM</td>
<td>0.0014</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.77)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\bar{U}v(3)$</td>
<td>-1.0891</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.58)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$TO$</td>
<td>1.6017</td>
<td>1.5973</td>
<td>1.6074</td>
<td>1.6389</td>
</tr>
<tr>
<td></td>
<td>(0.84)</td>
<td>(0.82)</td>
<td>(0.76)</td>
<td>(0.50)</td>
</tr>
<tr>
<td>$N$</td>
<td>5776</td>
<td>5776</td>
<td>5776</td>
<td>5526</td>
</tr>
</tbody>
</table>

The dependent variable in the regressions is the raw (non-detrended) aggregate open interest series. The independent variables are as described in the captions to Tables 2.6 and 2.8. Finite sample $t$ statistics, shown in parentheses, are computed under the null of cointegration between $OI$ and $TO$ with a cointegrating vector $(-1, 1.70)$. 

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REFERENCES


Joshi, Mark, 2007, The convergence of binomial trees for pricing the american put, Available at SSRN 1030143.


