Three Essays in Financial Economics

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By

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Dedication

For my parents, Carlos Cesar Julio and Lucia Cobresle who supported and encouraged me during their lifetime to pursue higher education and discover the sunlight pathways of hope and fulfillment.

For my many friends who never left my side and gave me all the support I needed while pursing my PhD and all my professors who believed in me and cheered me on all along the way.

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Abstract

Chapter 1. Campbell and Cochrane (CC, 1999) argue that their habit formation based stochastic discount factor is a recession state variable. In recessions, consumption falls closer to habit and both risk aversion and risk premia rise. The connection between discount factor and risk premia is more pronounced in bad times. Using the CC habit formation approach we construct a "recession" risk factor and tests the significance of this factor in the cross-section of asset returns, based on factor innovations and portfolios based on factor covariances.

Chapter 2. We investigate the profitability of momentum and contrarian portfolio strategies in a cross-section of broad futures markets. We identify 16 profitable momentum strategies that earn 33.64% average return a year and 16 profitable contrarian strategies that earn 10.69% average return a year. Overall, this indicates that relative-strength and contrarian strategies perform better on a risk-adjusted basis than passive long-only strategies in equity and futures markets, making futures markets contracts attractive candidates to be included in well-diversified portfolios.

Chapter 3. Banks face adverse selection or moral hazard problems in its lending activity that may lead to an inefficient allocation of credit which can be mitigated by expensive screening credit applications and by monitoring borrowers. A cheaper and more effective way to acquire information is by exchanging it with other lenders. We model information sharing in the banking industry within a network framework that provide us with some useful insights on the optimal number of credit sharing information alliances individual banks should establish to maximize expected profits. We find that if banks operate in independent markets, then it is optimal that each bank shares credit information with all the other banks. This is in line with the tendency of credit bureaus to be totally integrated in a few big credit agencies. In a homogeneous loan market, where banks compete a la Cournot, banks' profits are maximized at an intermediate level of sharing credit information. This provides an alternative explanation for why we observe syndicated loans even in countries in which formal sharing information systems are well established.

Key Words: habit formation models, risk premia, factor models, futures markets, trading strategies, network theory, banking.

Chapter 1:

Recession Risk Factor and the Cross-section of Expected Stock Returns

1. Introduction

There is no doubt that the consumption based asset pricing paradigm focused on the representative agent formulation is one of the major advances in financial economics theory during the last three decades. The seminal contribution of Lucas (1978), Breeden (1979), Grossman and Shiller (1981), show how consumption/saving decisions are linked to the equilibrium price of assets.

Unfortunately, the standard consumption-based model has been an empirical failure. The model has been mostly rejected using U.S. data in its representative agent formulation with time-separable power utility (Hansen and Singleton 1982, 1983). Moreover, it has performed no better and often worse than the simple static-CAPM [Mankiw and Shapiro (1986)] in explaining the cross-sectional pattern of asset returns. Campbell and Cochrane (2000) show in an explicit quantitative example that, in fact, portfolio-based models can outperform the canonical consumption-based model by the amount we see in the data, even when a slightly more complex consumption-based model holds by construction.

The consumption-based model has failed at explaining a number of asset pricing phenomena, including the high market Sharpe ratio (ratio of equity premium to the standard deviation of stock returns) simultaneously with stable aggregate consumption growth, the high level and volatility of the stock market returns, the low and relatively constant interest rates, the cross-sectional variation in expected portfolio returns, and the predictability of excess stock market returns over medium to long-horizon.

From all these failures, the equity premium puzzle and the risk-free rate puzzle are the two failures in particular that have attracted most of the attention among financial economists. Since the work of Mehra and Prescott (1986) and Hansen and Jagannathan (1991), researchers have altered the standard consumption-based models by workings backwards to some extent, characterizing the properties that discount factors must have in order to explain asset return data. Mainly, the modeling has been driven by the fact that we know that the stochastic discount factor had to be exceptionally volatile, while not too conditionally volatile and that the risk-free rate had to be relatively stable (Cochrane, (2001)).

The habit-formation model of Campbell and Cochrane (1999), building on work by Abel (1990) and Constantinides (1990), attack the equity premium and the risk free rate puzzle by modifying the representative agent's preferences. In particular, Campbell and Cochrane (1999) add a slow moving habit formation to the standard power utility function to obtain a consumption-based model which has some hope of explaining asset pricing data. They showed that high stock market volatility and predictability could be explained by a small amount of aggregate consumption volatility if it were amplified by time-varying risk aversion.

The main idea behind external habit formation models is that agents get used to a certain standard of living, which depends on the consumption of some exterior reference group, typically per capita aggregate consumption and that their overall well-being depends on how much can be consumed relative to this reference level. Thus, people are more risk averse as consumption and wealth decrease in a recession relative to some "habit" or the recent past.

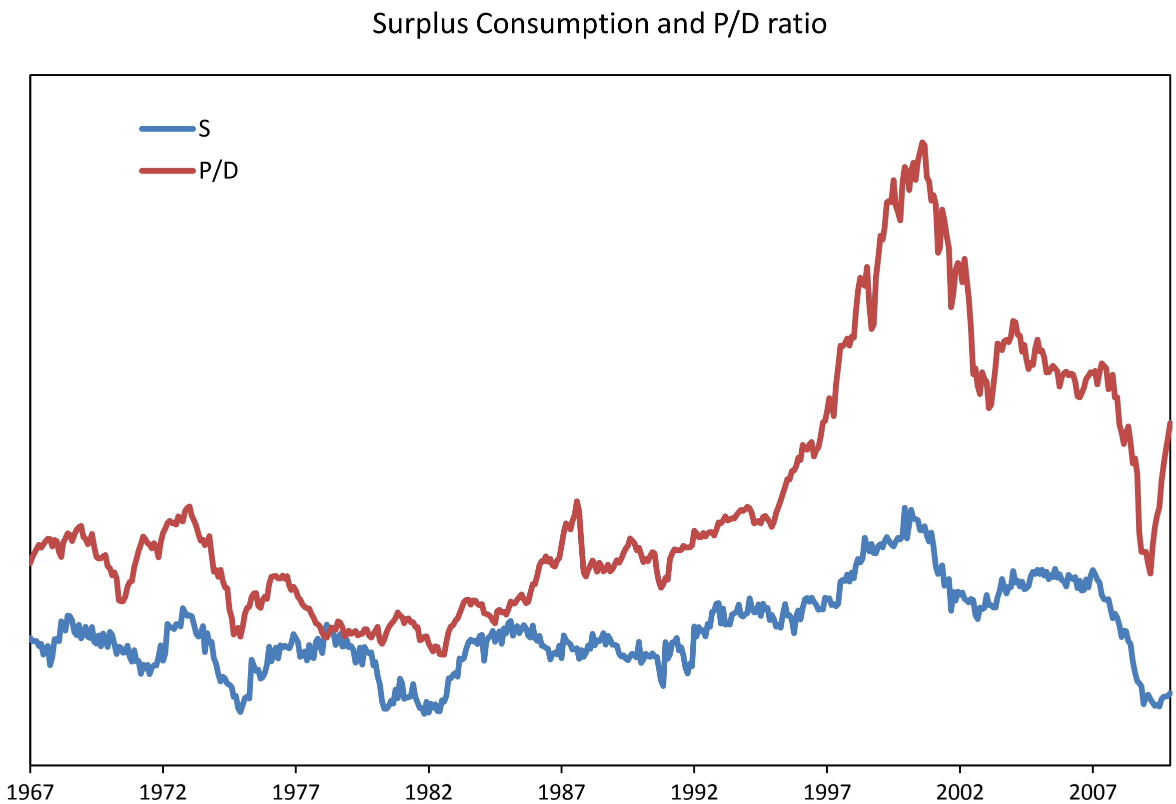
From the empirical research of risk premia and expected returns over the business cycle we know that expected stock returns are related to the business cycles as shown in papers by Fama (1990), Fama and French (1989) and Kandel and Stambaugh (1990). The later show that standard models with time-separable utility and exogenous endowment processes have a tendency to generate procyclical expected returns, which is at odds with the data that identifies risk premia as countercyclical - higher in recession when people are less willing to take systematic risks and lower in booms. The time-variation of risk premia remain as a central empirical fact that had to be linked to the pervasive business cycle. Clearly, the challenge is to choose a theory with coherent empirical prediction that tell us how to measure bad economic times and times of high risk premia.

In his 2011 AFA presidential address, John Cochrane (2011), highlights the importance of theories that link what he calls discount rates (risk premia) to macroeconomic events. Risk premia are high for those assets that tend to pay off poorly in bad economic times. Campbell and Cochrane's (1999) model looks promising at explaining these characteristics of asset pricing and aggregate economic performance. As bad shocks drive consumption down towards the habit level, risk aversion rises, stock prices decline, and expected returns rise. Since, habit adjusts slowly to consumption this means that at sufficient longer horizons the model has the ability to separates a fear of consumption declines from the stronger event fear of recession.

The following figure show in advance how the Campbell-Cochrane habit-based model to be presented in section 2 has the potential to explain the pattern followed by asset prices, even in the unusual event of a financial crisis. Figure 1 presents the surplus consumption ratio $S_t = (C_t - X_t)/C_t$ inferred from the habit specification model, where X_t is the habit level. Obviously, when consumption, C_t gets close to the habit level, X_t the investor/consumer is worse off. As we will see, the model predicts that the price-dividend ratio is a nearly log-linear function of the surplus consumption ratio (the only state variable of the model).

Figure 1. Surplus consumption and stock prices.

This figure plots the surplus consumption ratio and the S&P 500 price/dividend ratio. The surplus consumption ratio, $S_t = (C_t - X_t)/C_T$, captures the relation between consumption, C_t and habit levels, X_t, in which habit moves slowly in response to changes in consumption. The surplus consumption ratio increases with consumption. $S_t \rightarrow 0$, corresponds to an extremely bad state in which consumption is equal to habit; on the other hand, $S_t \rightarrow 1$ corresponds to an extremely good state in which consumption rises relative to habit.



We can observe that the general pattern is astonishingly good: when the surplus consumption ratio fell, stock prices fell. This is in contrast with the well known empirical failure of most of the standard consumption-based models, i.e. the actual low correlation between stock returns and consumption growth described by Cochrane and Hansen (1992). Thus, it seems that by introducing a small friction in the equilibrium consumption-based model, i.e. slow moving habits in the utility function, we can check or test the implication that consumption growth and stock expected returns are highly correlated with the surplus consumption ratio with some hope that the model will be useful explain asset return in a large cross-section of asset returns, and not only to match the variables at an aggregate level.

The model has changed the way we think about risk premia. Under the model's assumptions, the consumer will require a higher risk premia in times of low surplus consumption ratio. The habit model captures the fundamental idea that consumers become more risk averse as consumption drops during recessions. In this sense, variation across assets in expected returns is driven mainly by variation across assets in covariances with recessions far more than by variation across assets in covariances with consumption growth (Campbell and Cochrane, (1999)).

Surprisingly, few articles have tried to estimate and test the Campbell-Cochrane habit utility function on a cross section of stock returns, like for example in the Fama–French 25 size and book-to-market portfolios (Cochrane, 2008). The closest exception is Chen and Ludvigson (2009) which we summarized in the related literature section. The goal of this article is to construct a "recession factor" using the CC habit formation approach and test the significance of this factor in the cross-section of asset returns, based on factor innovations and portfolios based on factor covariances. In other words, this essay argues that the covariance between asset returns and the recession factor drives expected returns.

RELATED LITERATURE

As Cochrane (2008) argue, surprisingly, few articles have tried to estimate and test the Campbell-Cochrane habit utility function on a cross section of stock returns, like for example in the Fama–French 25 size and book-to-market portfolios. The closest exception is Chen and Ludvigson (2009). They pursue a semiparametric approach treating the functional form of the habit as unknown, and estimating it along with the finite dimensional parameters of the power utility function. Comparing models based on Hansen–Jagannathan (1997) distance, which is a sum of squared pricing errors weighted by the inverse of the second-moment matrix of returns, they find that the resulting internal habit SDF proxy can explain a cross-section of 6 size and book-market sorted portfolio equity returns better than the Fama–French three-factor model. Their empirical results also indicate that the estimated habit function is nonlinear and that habit formation is better described as internal rather than external habit formation. In the internal habit formation case, the habit is a function of the agent's own past consumption while in models of external habit formation the habit depends on the consumption of some exterior reference group, called by Abel (1990) "catching up with the Joneses", typically per capita aggregate consumption. In other structures, internal and external habits are observationally indistinguishable (Campbell and Cochrane, 1999), however, determining which form of habit formation is more empirically plausible might be important because the two specifications can have different implications for optimal tax policy and welfare analysis (Ljungqvist and Uhlig (2000)).

Tallarini and Zhang (2005) estimate the model proposed by Campbell and Cochrane (1999) and examine the cyclical behavior of expected stock returns in an equilibrium asset pricing model in which agents' preferences have an unobserved external habit using the efficient method of moments (EMM). The model, however, is still rejected at the 1% level. While the model performs reasonably well in matching the mean of returns, it fails to capture the higher-order moments.

Using GMM, Fillat and Garduno (2005) estimate and test the CC (1999) model under three different market settings: (1) complete consumption insurance, using aggregate consumption data, (2) limited stock market participation, using household-level data and (3) incomplete markets. They find that regardless of the market setting the model is rejected as it fails the null hypothesis that the Euler equation holds. However, they observed that the setting that better explains average stocks returns is the one with complete markets.

Santos and Veronesi (2010) argue based on a theoretical grounds that non-linear external habit persistence models generate counterfactual predictions in the cross-section of stock returns. In particular, they show that in the absence of cross-sectional heterogeneity in firms' cash-flow risk, these models produce a "growth premium". This implication is in conflict with the well-established empirical observation of a "value premium". However, the substantial heterogeneity in firms' cash-flow risk needed to generate both a value premium as well as most of the stylized facts about the cross-section of equity returns generates a "cash-flow risk puzzle" in the sense that value stocks must have an implausible cash-flow risk compared to the data to correct for the growth premium.

Lawrence, Geppert and Prakash (2009) paper tests whether the Campbell and Cochrane (1999) habit utility model generates a valid stochastic discount factor for the 25 Fama-French size/book-to-market and size/momentum sorted portfolios using quarterly consumption data. They test their model using the methodology of Hansen and Jagannathan (1991) and Burnside (1994). They find that for reasonable parameter values, the model's stochastic discount factor is inside the Hansen-Jagannathan bounds and therefore satisfies the necessary conditions for a valid stochastic discount factor.

This article takes a different approach to estimate and test the Campbell-Cochrane habit utility function model. First, we derive a valid a valid stochastic discount factor from the Campbell and Cochrane (1999) habit utility model. Then, using this discount factor we construct a "recession factor" and test if this new factor can explain the 25 Fama-French size/book-to-market and size/momentum sorted portfolios using monthly consumption data.

The paper is organized as follows. In Section 2 we describe the Campbell and Cochrane habit utility model. We provide details on the data and the construction of our recession factor (Stochastic Discount Factor) in Section 3 and in Section 4 we present details of the results. We discuss the results in Section 5 and the paper ends with a brief conclusion, as Section 6.

2. The model

Assume that the discount factor or *sdf*, M_t, and gross returns, R_t, are jointly lognormal distributed.

$$E_{t-1}(M_t R_t) = E_{t-1}\left[e^{\ln(M_t R_t)}\right] = E_{t-1}\left[e^{ln(M_t)+ln(R_t)}\right] = E_{t-1}\left[e^{(m_t+r_t)}\right]$$

Define $Z = M_t R_t$ and $z = ln(Z) = \ln(M_t R_t) = ln(M_t) + ln(R_t) = m_t + r_t$. Using the normal property $E(e^z) = e^{E(z)+.5\sigma^2(z)}$ we have

$$E_{t-1}(M_t R_t) = E_{t-1}\left[e^{(m_t+r_t)}\right] = e^{E_{t-1}(m_t+r_t)+\frac{1}{2}[\sigma^2_{t-1}(m_t+r_t)]}$$

Then the law of one price states that

$$E_{t-1}(M_tR_t) = E_{t-1}\left[e^{(m_t+r_t)}\right] = e^{E_{t-1}(m_t)+E_{t-1}(r_t)+\frac{1}{2}[\sigma^2_{t-1}(m_t)+\sigma^2_{t-1}(r_t)+2cov_{t-1}(m_t,r_t)]} = \alpha_t$$

where $\alpha_t = 1$ which rules out under or over pricing. Taking logs we find

$$ln(E_{t-1}[M_tR_t]) = E_{t-1}(m_t) + E_{t-1}(r_t) + \frac{1}{2}[\sigma^2_{t-1}(m_t) + \sigma^2_{t-1}(r_t) + 2cov_{t-1}(m_t, r_t)] = \alpha^*_t$$

where small letters denote logs and defining $\alpha^*_t = ln(\alpha_t)$.

The risk free rate is given by

$$R_{f,t} = \frac{1}{E_{t-1}(M_t)}$$

Then the log of the risk free rate is,

$$r_{f,t} = ln(R_{f,t}) = ln\left(\frac{1}{E_{t-1}(M_t)}\right) = -ln(E_{t-1}(M_t)) = -E_{t-1}(m_t) - .5\sigma^2_{t-1}(m_t)$$

Combining now, expected returns are,

$$E_{t-1}(r_t) - r_{f,t} = \alpha^*_t - .5\sigma^2_{t-1}(r_t) - cov_{t-1}(m_t, r_t)$$

The variance term is from Jensen's Inequality. The form of *sdf,* m_t , in the covariance term either is derived from projection on returns data or the intertemporal marginal rate of substitution (*IRMS*) of a specific utility framework.

$$m_t = \ln\left(\beta \frac{u'(c_t)}{u'(c_{t-1})}\right)$$

Campbell and Cochrane (CC,1999) derive *sdf,* m_t , from a Habit formation utility and log normality where model agents maximize the utility

$$E\sum_{t=0}^{\infty}\delta^t\frac{(C_t-X_t)^{1-\gamma}-1}{1-\gamma} \tag{A5}$$

where X_t the level of habit that responds slowly to past consumption, δ is the time preference, and γ is a curvature parameter. This framework offers much richer dynamics than the standard utility model such as time varying risk premia and uses local curvature of the utility function to increase the volatility of the discount factor which is key to success to pricing assets for which conventional models fall woefully short. For convenience, utility is recast in terms of the surplus consumption ratio

$$S_t=\frac{C_t-X_t}{C_t}, S=\{0,1\} \tag{A6}$$

where if it goes to zero consumption becomes equal to habit. it is easier to model the log of this ratio instead of modeling X_t itself. The surplus consumption ratio is also called the "recession" state variable as "good" and "bad" states are defined by how far consumption strays from habit.

CC assume that log consumption follows a random walk with drift g and an $i.i.d.$ innovation ν_t,

$$\Delta c_t = g+\nu_t,\ \ \nu_t \sim i.i.d.N(0,\sigma) \tag{A7}$$

CC model Log S_t as an AR(1) square root process:

$$s_t=(1-\phi)\bar{s}+\phi s_{t-1}+\lambda(s_{t-1})\nu_t \tag{A8a}$$

$$\Delta s_t=(1-\phi)(\bar{s}-s_{t-1})+\lambda(s_{t-1})\nu_t \tag{A8b}$$

where $\bar{S}=\sigma\sqrt{\gamma/(1-\phi)}$ is the steady state value of the surplus consumption ratio. The parameter ϕ governs the persistence of the log surplus consumption ratio, while the sensitivity function $\lambda(s_{t-1})$ control the sensitivity of s_{t+1} and thus of log habit x_{t+1} to innovations in consumption growth v_t .

The sensitivity function is

$$\lambda(s_{t-1}) = \frac{1}{\bar{S}}\sqrt{1-2(s_{t-1}-\bar{s})} - 1, \text{for } s_{t-1} \leq \mathrm{s_{max}}, \text{and 0 otherwise} \tag{A9a}$$

where

$$\mathrm{s_{max}} = \bar{s} + .5(1-\bar{S}^2) \tag{A9b}$$

The features of this process ensure consumption remains above habit, habit moves positivity with consumption, a countercyclic price of risk, habit has no influence on steady state consumption growth, and a constant risk free rate.

The specific *sdf* is placed into the generic present value relation:

$$\frac{P_{t-1}}{\Pi_{t-1}} = E_{t-1}\left(M_t^* \frac{X_t}{\Pi_t}\right) \rightarrow E_{t-1}\left(M_t^* \frac{\Pi_{t-1}}{\Pi_t} R_t\right) = E_{t-1}(M_t R_t) = 1 \tag{A10a}$$

where P_{t-1} is the nominal price of the payoff X_t divided by the price levels at each date and R_t is the nominal gross return and the nominal for of the habit formation discount factor is

$$M_t = \delta\left(\frac{S_t}{S_{t-1}}\frac{C_t}{C_{t-1}}\right)^{-\gamma} \frac{\Pi_{t-1}}{\Pi_t} = \delta e^{-\gamma[\Delta s_t + \Delta c_t] - \pi_t} \tag{A10b}$$

Let inflation also be *i.i.d.*:

$$\pi_t = \tau + \eta_t, \;\; \eta_t \sim i.i.d.\, N\left(0, \sigma_\eta^2\right) \tag{\#}$$

Now the Log discount factor is

$$m_t = ln(\delta) - \gamma[\Delta s_t + \Delta c_t] - \pi_t$$
$$m_t = ln(\delta) - \gamma[(1-\phi)(\bar{s} - s_{t-1}) + \lambda(s_{t-1})v_t + g + v_t] - \tau - \eta_t \tag{\#}$$

with expectation and deviation are respectively

$$E_{t-1}(m_t) = ln(\delta) - \gamma[(1-\phi)(\bar{s} - s_{t-1}) + g] - \tau$$
$$dm_t = m_t - E_{t-1}(m_t) = -\gamma[\lambda(s_{t-1}) + 1]v_t - \eta_t \tag{\#}$$

and variance

$$\sigma_{t-1}^2(m_t) = E_{t-1}[m_t - E_{t-1}(m_t)]^2 = E_{t-1}[-\gamma[\lambda(s_{t-1}) + 1]v_t - \eta_t]^2$$
$$= \gamma^2[\lambda(s_{t-1}) + 1]^2\sigma_c^2 + \sigma_\eta^2 + \ 2\gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t) \tag{\#}$$
$$= \gamma(1-\phi)\big(1 - 2(s_{t-1} - \bar{s})\big) + \sigma_\eta^2 + \ 2\gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t)$$

and log of the expected value is

$$ln\big(E_{t-1}(M_t)\big) = E_{t-1}(m_t) + \frac{1}{2}\sigma_{t-1}^2(m_t)$$
$$= ln(\delta) - \gamma(1-\phi)(\bar{s} - s_{t-1}) - \gamma g - \tau$$
$$+\frac{1}{2}\Big(\gamma(1-\phi)\big(1 - 2(s_{t-1} - \bar{s})\big) + \sigma_\eta^2 + \ 2\gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t)\Big) \tag{\#}$$
$$= ln(\delta) - \gamma g - \tau + \frac{1}{2}\gamma(1-\phi) + \frac{1}{2}\sigma_\eta^2 + \ \gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t)$$

with risk free rate

$$r_{f,t} = -ln\big(E_{t-1}(M_t)\big)$$
$$= -ln(\delta) + \gamma g + \tau - \frac{1}{2}\gamma(1-\phi) - \frac{1}{2}\sigma_\eta^2 - \ \gamma[\lambda(s_{t-1}) + 1]E(v_t, \eta_t) \tag{\#}$$

that is constant if real consumption growth and inflation are uncorrelated

$$r_{f,t} = -ln\big(E_{t-1}(M_t)\big) = -ln(\delta) + \gamma g + \tau - \frac{1}{2}\gamma(1-\phi) - \frac{1}{2}\sigma_\eta^2 \qquad (\#)$$

The covariance term is

$$cov_{t-1}(m_t, r_t) = E_{t-1}([m_t - E_{t-1}(m_t)][r_t - E_{t-1}(r_t)])$$

$$cov_{t-1}(m_t, r_t) = E_{t-1}\big[(-\gamma[\lambda(s_{t-1}) + 1]v_t - \eta_t)\big(r_t - E_{t-1}(r_t)\big)\big]$$

$$= -\gamma[\lambda(s_{t-1}) + 1]E_{t-1}(v_t, r_t) - E_{t-1}(\eta_t, r_t) \qquad (\#)$$

$$= -\gamma[\lambda(s_{t-1}) + 1]E(v_t, r_t) - E(\eta_t, r_t)$$

$$E_{t-1}(r_t) - r_{f,t} = \alpha_t^* - .5\sigma_{t-1}^2(r_t) + \gamma[\lambda(s_{t-1}) + 1]E(v_t, r_t) + E(\eta_t, r_t). \qquad (\#)$$

$$E_{t-1}(r_t) = 1 - \sqrt{1 - 2\gamma[\lambda(s_{t-1}) + 1]E(v_t, r_t) - 2E(\eta_t, r_t) + E(r_t)^2 - 2r_{f,t}}. \qquad (\#)$$

Because the expectation involve the conditional variance we pick the root that yields expected returns under 100%. The expost formulation used in estimation is

$$r_t - r_{f,t} = -.5[r_t - E_{t-1}(r_t)]^2 + \gamma[\lambda(s_{t-1}) + 1]v_t r_t + \eta_t r_t. + \varepsilon_t \qquad (\#)$$

$$r_t - r_{f,t} = -.5[r_t - E_{t-1}(r_t)]^2 - dm_t r_t + \varepsilon_t \qquad (\#)$$

with risk free

$$r_{f,t} = -ln(\delta) + \gamma g + \tau - .5\gamma(1-\phi) - .5\sigma_\eta^2 - \gamma[\lambda(s_{t-1}) + 1]v_t\eta_t + \xi_t \qquad (\#)$$

The standard CRRA model results if $\lambda(s_{t-1}) = 0$, and $\phi = 1$.

There are certainly many ways to parameterize our *sdf* M_t to match the average market rate of return and risk premium over the last 50 years. For convenience, we estimate the following moment conditions:

$$E\begin{bmatrix}\varepsilon_t\\ \xi_t\end{bmatrix}=\begin{bmatrix}0\\ 0\end{bmatrix}, \tag{\#}$$

where $\mathrm{r}_t$is the value weighted CRSP index return, $r_{f,t}$ is the 1-month t-bill rate as given by Kenneth French's website. The *sdf* M_t is constructed (eqs. A10) from monthly *real* percapita personal consumption without durables and the price index of all personal consumption expenditures for computing real consumption and inflation. The parameters δ and γ are estimated and ϕ is held constant.

The starting value for surplus consumption is held at its steady state value ($s_0 = \bar{s}$) and updated with changes in γ with the consumption growth mean, g, and its standard deviation , σ_c^2, coming come from time series data. The moment conditions are then iterated until parameters and the process for surplus consumption converges.

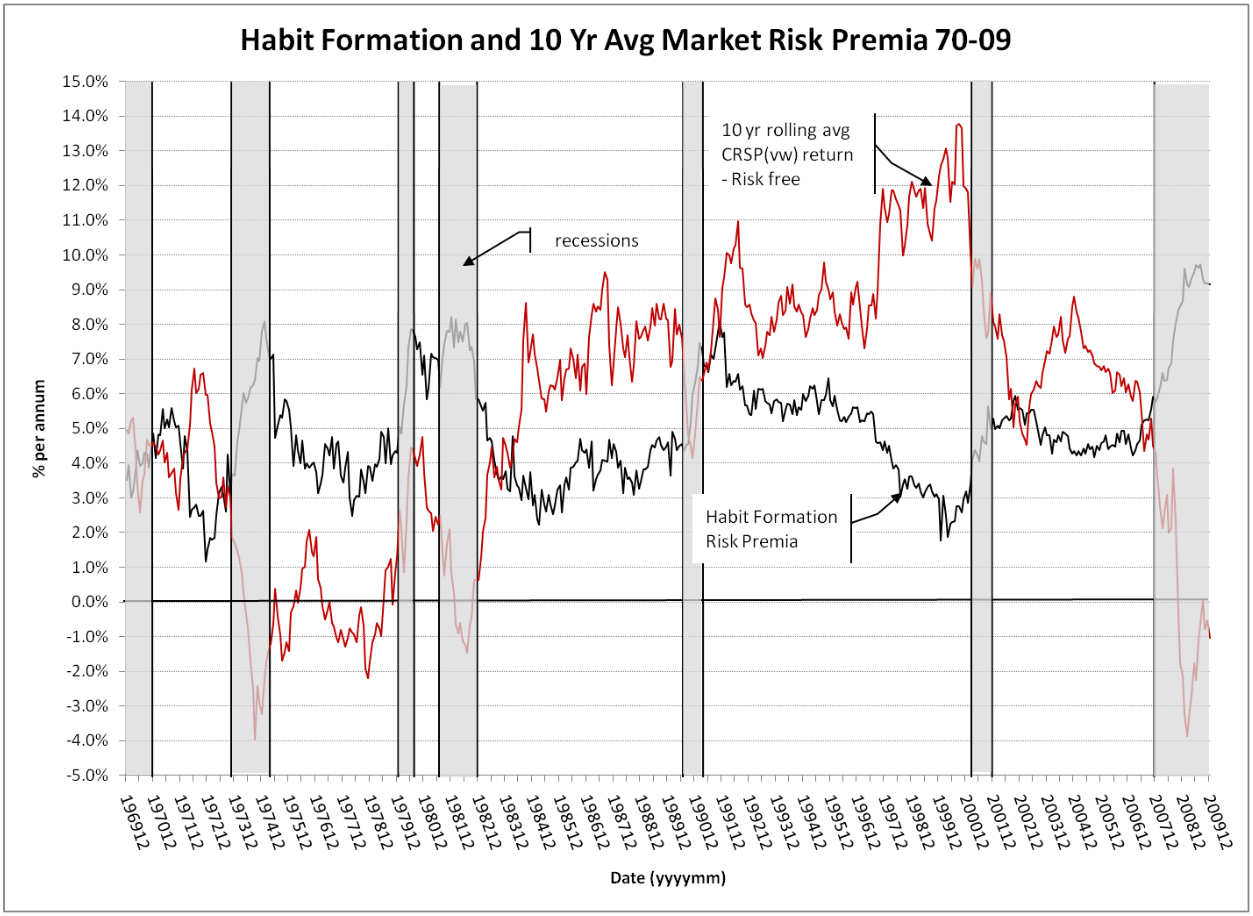
The first moment condition guarantees the discount factor reproduces the average rate on the market, but does not fix the premium. The second moment is the definition of the risk free rate which then fixes the premium. In the spirit of minimum variance, the persistence parameter ϕ is chosen to maximize the Sharpe ratio $\frac{E(R^e)}{E(\sigma^e)}$ or the variance of the discount factor $\frac{\sigma_m}{E_m}$ needed to price the market and still fit the risk premium.[1]

3. Estimation results

In the following figure, we can see how expected excess stock returns (risk premia) and realized excess returns are related to the business cycles. Shaded areas indicated US recessions.

[1] We tried to estimate the system with a third moment condition to fix the Sharpe ratio and estimate ϕ from: $\sigma_m/E_m = c$, but found it gave two solutions because the steady state value of surplus consumption is a function of both γ and ϕ and variance of the discount factor is affected by both. Higher value of ϕ dampens variance resulting in failure to converge if the value is too high for the system to fit both conditions.

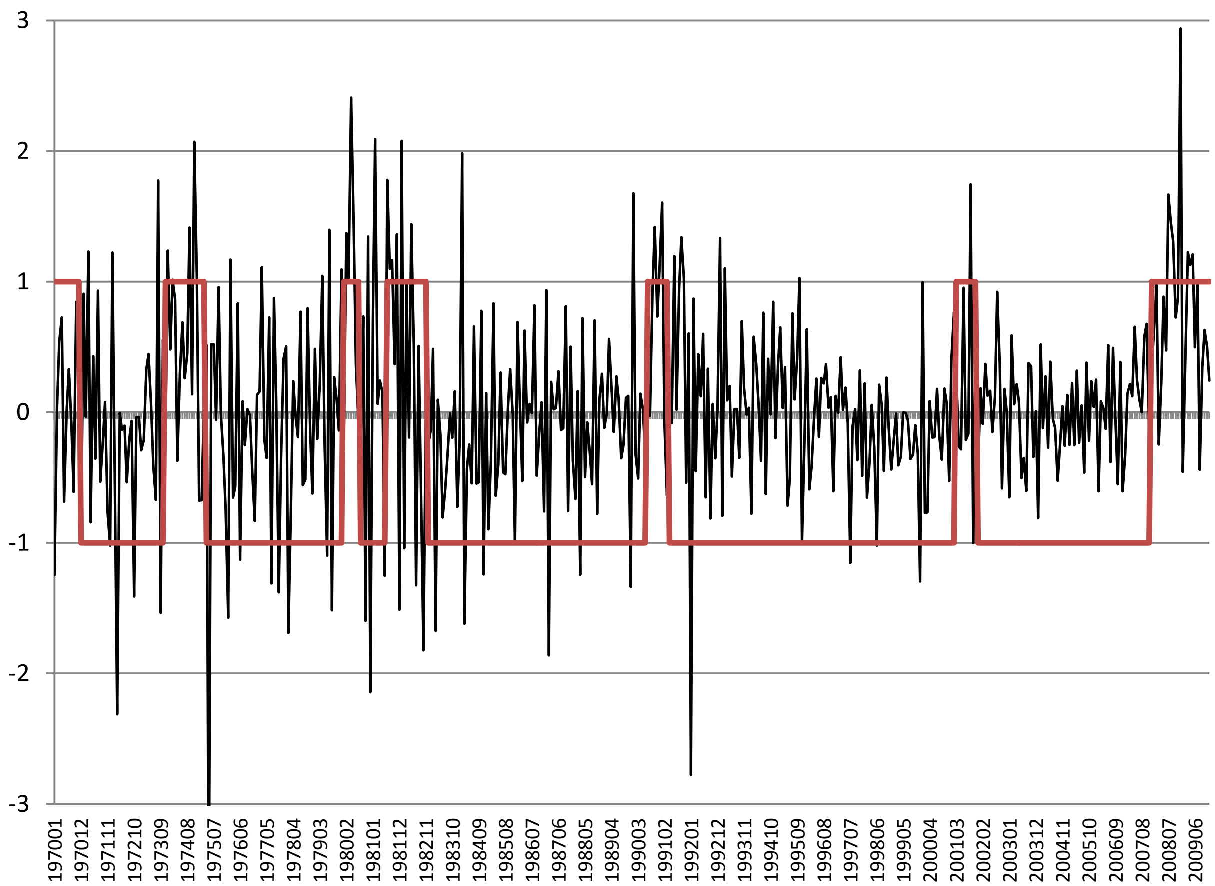
Note that the risk premia derived from the habit formation model increase in every period in which the economy had enter in a recession period. Campbell and Cochrane's (1999) model shows that as consumption drops towards the habit level, risk aversion rises, stock prices decline, and risk premia rise. Since, habit adjusts slowly to consumption this means that at sufficient longer horizons the model has the ability to separates a fear of consumption declines from the stronger event fear of recession.



Moreover, the increase in risk premia we observed in bad economic times is inversely related to the actual excess return given by the ten-year rolling average CRSP value-weighted market excess return. To see what this is the case, imagine an average investor of the type buy and hold for the covered period 1969-2009. In a period of recession, actual excess return must necessarily fall (stock prices drops) in order for the risk premia to rise. If stock prices fall, we expect long run investors to run in and buy. The graphs suggests why they do not - their discount rate (or the expected risk premia) rises in a recession.

Empirical Features of the "Recession" Measure

As illustrated below, the One interesting characteristic of the recession series plotted in the next figure are its occasional upward spikes, indicating months with especially high estimated recession risk. Many of these spikes occur during market downturns.



A negative shock to consumption growth means less consumption is around at date=t than expected leading to a higher actual price (i.e., higher marginal utility) at this date corresponding to the positive deviations during recession in the graph.

The largest upward spike in our measure of recession risk occurs in December 2008, after the bursting of the housing bubble in the summer of 2007 that lead to a run in the so called shadow banking system (Gorton, 2010). While the overall mortgage losses are large on an absolute scale, they are still relatively modest compared to the $8 trillion of U.S. stock market wealth lost between October 2007, when the stock market reached an all-time high, and October 2008 (Brunnermeier, 2008).

If that panic had not occurred, it is likely that any economic contraction following the housing bust would have been no worse than the mild 2001 recession that followed the dot-com bust (Cochrane, 2008) which coincided with the sharp rise of the estimated recession risk in September, 2001. In the same way, the recession of 1990 associated with the invasion of Kuwait by Iraq have an increase on the recession risk of the same magnitude. The second largest spike is early, 1980's associated with the disinflationary twin recessions. The Third largest positive value in our measure of recession risk is in the recession of 1973-5, associated with the first OPEC price increases (Stock and Watson, 1999). In the other hand, we can see that the negative values for our measure of recession risk is correspond to the long expansions of the 1980's and the early 1990's.

The Data

Consumption Data: Several studies use quarterly US consumption data because it contains fewer measurement errors than monthly consumption data. See Ferson and Constantinides (1991) and Heaton (1995) for more details. However, to be consistent with the empirical literature on the cross-section of returns, we use consumption at a monthly frequency. We measure aggregate consumption data as seasonally adjusted monthly expenditures on non-durable goods and services. Personal consumption per capita is obtained by dividing the aggregate by a monthly measure of the US population. Finally, real per capita consumption is obtained by dividing the latter by the monthly price index for personal consumption expenditures (base 2005=100) , all of which were obtained from records of the Bureau of Economic Analysis and the Census Bureau of the U.S. Department of Commerce. The size of the sample in this case is the biggest, such that data were available for consumption, population, returns, and inflation ranging from
January 1959 to December 2009.

Asset Returns: For asset returns we use the following US monthly data: Six size/book-market portfolio returns from January 1959 to December 2009. The portfolios are constructed at the

end of each June, are the intersections of two portfolios formed on size (market equity, ME) and three portfolios formed on the ratio of book equity to market equity (BE/ME). The size breakpoint for year t is the median NYSE market equity at the end of June of year t. BE/ME for June of year t is the book equity for the last fiscal year end in $t-1$ divided by ME for December of $t-1$. The BE/ME breakpoints are the 30th and 70th NYSE percentiles. Data is taken from Kenneth French's website: *http*
://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html.

In addition, we reevaluate the model using 25 size/book-market portfolio returns from January 1959 to December 2009.

Sorting Portfolios and Recession Risk Factor

We argue that recession risk is in fact a priced factor and we expect that the risk premium associated with it to be quantitatively significant. Following the empirical literature, we now routinely form portfolios by sorting them by some characteristic, in particular by the covariance between stock returns and the recession factor derived from the habit formation model. Then we run time-series regressions like CAPM or Fama and French's to see which factors explain the spread in average returns, as revealed by small regression intercepts.

In other words, we ask the question whether a stock's expected return is related to the sensitivity of its return to the innovation in our recession factor derived from the habit formation stochastic discount factor, DM_t. That sensitivity, denoted for stock i by its loading factor β_i^{DM} is the slope coefficient on DM_t in a multiple regression in which the other independent variables are additional factors given by different models of asset pricing.

Economic recession and risk premiums: Stocks

In this section we investigate whether our economic recession risk is a priced state variable. In particular we test whether DM is related to the cross-section of U.S. portfolio returns. In others words, we explore whether there is evidence consistent with the well-known fact that investors find economic downturn undesirable. We expect that investors will require a compensation for holding stock portfolios with greater exposure to that risk, i.e., performing more poorly in bad economic times.

In our discussion above we argued that the expected-return premium associated with the recession risk is positive. Here we explore this conjecture by employing the multivariate asset pricing model in Pastor and Stambaugh (2003). This model allows assessing the marginal contribution of DM to the cross-section of equity portfolio returns while accounting for their sensitivities to other factors.

Define the multivariate regression for each portfolio i as:

$$r_t = \beta_0 + BF_t + \beta^{DM} DM_t + e_t, \qquad \forall t, \qquad (\#)$$

where r_t is a $N \times 1$ vector containing the excess returns on the N's portfolios, F_t is a $K \times 1$ vector containing the realizations of the "traded" factors, i.e. MKT, SMB, HML and MOM. B is a $N \times K$ matrix of factor loadings, and β_0 and β^{DM} are $N \times 1$ vectors. In our case, we also consider a specification with only Fama-French three traded factors, excluding MOM.

Assuming that the N portfolios are priced by the returns' sensitivities to the traded factors and the non-traded recession factor, we would expect that

$$E(r_t) = B\lambda_F + \beta^{DM}\lambda_{DM}, \qquad (\#)$$

However, like Pastor and Stambaugh, we argue that while the vector of premia on the traded factors, λ_F˘ is equal to $E(F_t)$, the economic recession factor DM_t is not the payoff on a traded position, so in general the recession risk premium λ_{DM} is not equal to $E(DM_t)$, $\lambda_{DM} \neq E(DM_t)$.

Now, taking expectations of both sides of equation (#)

$$E(r_t) = \beta_0 + BE(F_t) + \beta^{DM} E(DM_t)$$

and substituting from equation (15) gives

$$\beta_0 + BE(F_t) + \beta^{DM} E(DM_t) = B\lambda_F + \beta^{DM}\lambda_{DM}$$

Since $E(F_t) = \lambda_F$ and $E(L_t) \neq \lambda_L$ in general, we obtain the following restriction

$$\beta_0 + \beta^{DM} E(DM_t) = \beta^L \lambda_{DM}$$

or equivalently,

$$\beta_0 = \beta^{DM}[\lambda_{DM} - E(DM_t)], \qquad (16)$$

We estimate λ_{DM} using the Generalized Method of Moments (GMM) of Hansen (1982). Let θ_p denote the set of unknown parameters: $\lambda_{DM,1\times 1}, \beta^{DM}_{N\times 1}, \mathrm{B}_{(N\times K)\times 1}$ and $E(DM_t)_{1\times 1}$, where $p = 2 + N(K \times 1)$ parameters and $g_t(\theta) = g(\theta, w_t.)$ is a $q \times 1$ vector of functions of θ and data $w_{t.}$ called a moment function, specifically we define $g_t(\theta)$ as:

$$g_t(\theta) = \begin{bmatrix} x_t \otimes e_t \\ DM_t - E(DM_t) \end{bmatrix}, \qquad (17)$$

where

$$x_t' = [1 \quad F_t' \quad DM_t]$$

$$e_t = r_t - \beta^L[\lambda_{DM} - E(DM_t)] - BF_t - \beta^{DM} DM_t, \qquad (18)$$

Let's define also $\bar{g}_T(\theta) = \left(\frac{1}{T}\right)\sum_{t=1}^{T} g_t(\theta)$ as the sample mean of $g_t(\theta)$. Then, the GMM estimator of θ minimizes $T\sum_{t=1}^{T} \bar{g}_T(\tilde{\theta})' \hat{V}_t^{-1} \bar{g}_T(\tilde{\theta})$ where $\hat{V}_T$ is a consistent estimator of the weighting matrix.[2]

Estimating the Premium: Multivariate DM beta estimation using 25 Fama-French Size/Book-to-market portfolios

We begin by studying the exposure of US 25 equity market portfolios formed to 25 U.S. portfolios formed on size (market equity) and book-to-market (book equity to market equity), from French's website to the economic recession risk factor, via the multivariate GMM procedure we have just described.

We explore if our measure of recession risk is able to priced popular traded portfolios, like the 25 Fama-French Size/Book-to-market portfolios. Specifically, Table 1 reports GMM estimates of λ_{DM} when accounting for the sensitivity of these portfolios' excess returns to the three traded Fama-French factors (U.S. market [MKT], size [SMB], and book-to-market [HML]) and four traded factors (Fama-French 3 factors plus momentum [MOM]), over the full sample 1967-2009 and two sub-periods (1967-1988, 1989-2009).

[2] Hansen (1982) showed that when the $w_t.$ are independent over t, $\hat{V}_T = V_T(\hat{\theta}) = \frac{1}{T}\sum_{t=1}^{T} g_t(\hat{\theta}) g_t(\hat{\theta})'$ is a consistent estimator of the weighting matrix wherer $\hat{\theta}$ is any consistent estimator

The table reports estimates of annualized percentage of the risk premium (λ_{DM}, multiplied by 12) associated with the DM recession factor for multivariate DM betas (β_i^{DM}) of both value- (Panel A) and equal-weighted (Panel B) 25 US portfolios formed on size (market equity) and book-to-market (book equity-to-market equity.

Table 1. DM Recession risk premiums and its contribution to the FF 25 US portfolios formed on size (market equity) and book-to-market (book equity-to-market equity) Expected Return

This table reports estimates of annualized percentage of the risk premium (λ_{DM}, multiplied by 12) associated with the DM recession factor for multivariate DM betas (β_i^{DM}) of value- (Panel A) and equal-weighted (Panel B) 25 US portfolios formed on size (market equity) and book-to-market (book equity-to-market equity), from French's website. Specifically, the table reports GMM estimates of λ_{DM} when accounting for the sensitivity of these portfolios' excess returns to the three traded Fama-French factors (U.S. market [MKT], size [SMB], and book-to-market [HML]) and four traded factors (Fama-French 3 factors plus momentum [MOM]), over the full sample 1967-2009 and two sub-periods (1967-1988, 1989-2009). We also report estimates of risk premiums per average DM beta ($\lambda_{DM}\overline{\beta_{\iota,DM}}$) and for the 10-1 spread portfolio (going long decile 10 stocks and short decile 1 stocks, $\lambda_{DM}(\beta_{10}^{DM} - \beta_1^{DM})$). Besides, the estimates of the risk premium associated with the recession factor λ_{DM} the table also reports the estimates of risk premiums per average DM beta ($\lambda_{DM}\overline{\beta_{\iota,DM}}$). The premium is reported as a monthly value multiplied by 1,200, so that the product of the average recession beta and the reported premium can be interpreted as the annual percentage return. The asymptotic t-statistics are in parentheses. Asymptotic t-statistics are in parentheses. J-test is the asymptotic chi-square statistic for the over-identifying restriction; the corresponding p-values are below.

	1967 - 2009		1967 - 1988		1989 - 2009	
	FF 3 Factor	FF 4 Factor	FF 3 Factor	FF 4 Factor	FF 3 Factor	FF 4 Factor
	Panel A: Value-weighted portfolios					
λ_{DM}	0.12	0.84	0.25	0.29	4.73	6.64
	(1.95)	(1.64)	(1.95)	(2.11)	(7.73)	(6.95)
$\lambda_{DM}\overline{\beta_{\iota,DM}}$	0.15	0.38	0.32	0.38	0.77	0.78
	(1.95)	(1.69)	(1.92)	(2.05)	(4.71)	(3.18)
$J-test$	24.57	87.88	34.96	27.85	27.67	30.12
	(0.99)	(0.13)	(0.99)	(0.99)	(0.99)	(0.98)
	Panel B: Equal-weighted portfolios					
λ_{DM}	10.60	11.46	0.49	2.75	10.69	42.61
	(7.04)	(5.92)	(2.08)	(2.99)	(13.42)	(2.62)
$\lambda_{DM}\overline{\beta_{\iota,DM}}$	0.77	2.27	0.59	1.18	0.72	2.99
	(1.86)	(4.93)	(2.13)	(2.87)	(1.95)	(2.91)
$J-test$	37.10	38.11	53.92	26.69	19.82	11.08
	(0.89)	(0.87)	(0.96)	(0.32)	(0.99)	(0.99)

The full-period estimate of λ_{DM} is significantly positive for both sets of portfolios under both specifications (three traded factors or four). Notice that the estimates of annualized percentage of the risk premium is substantially higher for equal-weighted than for value weighted portfolios for all the periods considered. For instance, for the period 1967-2009 λ_{DM} ranges between 10.60% and 11.46% for the equal-weighted portfolio using a three- factor and a four-factor model respectively. On the other hand, for the same period, λ_{DM} ranges between 0.12% and 0.84% annual for the value-weighted portfolio. The subperiod estimates are all positive, and the majorities are statistically significant.

We also report estimates of risk premiums per average DM beta ($\lambda_{DM}\overline{\beta_{\iota,DM}}$) as a monthly value multiplied by 1,200, so that the product of the average recession beta and the reported premium can be interpreted as the annual percentage return. For instance, DM recession risk premiums per average DM beta range between 0.59% and almost 3% annual for all the period considered for the equal-weighted portfolio.

Portfolio construction sorting by the economic recession betas

Motivated by the evidence in the previous section, we follow a portfolio-based approach similar to the one in Pastor and Stambaugh (2003) to construct a financial recession factor. At the end of every year of our sample, starting with 1967, we sort all stocks into ten portfolios based on stocks' estimated DM betas over the previous three years of monthly returns continuing through the current year end. We then regress the ensuing stacked, post-formation returns on the following standard asset pricing factors. According to the literature, estimated nonzero alphas would suggest that DM betas explain a component of expected stock returns not captured by standard factor loadings.

Our dataset comes from the monthly tape of the Center for Research in Security Prices (CRSP). It comprises monthly stock returns and values for all domestic ordinary common stocks (CRSP share codes 10 and 11) traded on the NYSE, AMEX, and NASDAQ between January 1, 1967 and December 31, 2009, with at least three years of monthly returns continuing through the current year end and with the restriction that stock prices should be between \$5 and \$1,000. At the end of each year (e.g., on month k), for each stock i with at least 36 months of available data through k we estimate its DM beta as the slope coefficient β_i^{DM} in the following multivariate regression of its monthly excess return $r_{i,k}$:

$$r_{i,k} = \beta_i^0 + \beta_i^{MKT} MKT + \beta_i^{SMB}[SMB_t] + \beta_i^{HML}[HML_t] + \beta_i^{MOM}[MOM_t] + \beta_i^{DM} DM_t + \epsilon_{i,t}$$

where MKT, SMB, and HML are the popular market, size, and book-to-market traded factors of Fama and French (1993); MOM is the traded momentum factor and DM is our economic recession factor, DM derived from the CC habit formation model.

We then sort all stocks by their pre-ranking, historical DM betas into ten portfolios (from the lowest, 1, to the highest, 10), and compute their value-weighted returns for the next twelve months. The resulting value-weighted decile portfolio returns for the next 12 months are stacked across years to generate post-ranking return series. Equally-weighted portfolios yield similar inference.

Unfortunately, as we can observed in Panel A of Table 2, the post-ranking recession betas do not follow a monotonic pattern across deciles, which is not consistent with the objective of the sorting procedure. The "10–1" spread, which goes long decile 10 (stocks with high recession betas) and short decile 1 (stocks with low recession betas), has a recession beta of 0.15, for the sub-period 1967-1988 with a *t*-statistic of 0.94. However, this suggest that beta might be time varying. Therefore, the coefficients used in the sort procedure are not stable over time.

Panel B of Table 2 reports some additional properties of portfolios sorted by historical recession betas. It reports the decile portfolios' betas with respect to the Fama-French factors, MKT, SMB, and HML, and the previously described momentum

Table 2. Properties of value-weighted portfolios of U.S. stocks sorted on historical DM recession betas

This table reports post-ranking properties of value-weighted portfolios of U.S. stocks sorted by their historical DM recession betas into ten equal portfolios from the lowest (1) to the highest (10), as well as for the 10-1 spread portfolio going long decile 10 stocks and short decile 1 stocks, over the full sample 1967-2009 and two sub-periods (1967-1988, 1989-2009). Eligible stocks are defined as ordinary common shares traded on the NYSE, AMEX, or NASDAQ with at least three years of monthly returns continuing through the current year end and with stock prices between \$5 and \$1,000. Stocks then are sorted in ten deciles of their historical MD recession betas β_i^{DM} from a multivariate regression of their percentage monthly excess returns on our economic recession factor, DM, the three traded Fama-French factors (U.S. market [MKT], size [SMB], and book-to-market [HML], from French's website), and the traded momentum factor (MOM, also from French's website). The resulting value-weighted decile portfolio returns for the next 12 months are stacked across years to generate post-ranking return series. Panel A reports their estimated post-ranking MDI betas from the aforementioned multivariate regression model. Panel B reports the time-series mean of each of these portfolios' value-weighted average of their post-ranking factor betas. The t-statistics are in parentheses.

	Decile Portolio										
	1	2	3	4	5	6	7	8	9	10	10-1
	Panel A: Post- Ranking DM betas										
1967-2009	0.07	0.02	-0.07	0.07	0.07	-0.05	0.01	-0.09	-0.05	0.03	-0.04
	(0.66)	(0.24)	(-0.69)	(0.78)	(0.84)	(-0.51)	(0.08)	(-1.03)	(-0.52)	(0.22)	(-0.26)
1967-1988	0.15	0.07	-0.02	0.07	0.06	0.01	-0.01	-0.05	-0.04	0.29	0.15
	(1.35)	(0.74)	(-0.23)	(0.71)	(0.59)	(0.10)	(-0.14)	(-0.57)	(-0.40)	(2.55)	(0.94)
1989-2009	-0.23	-0.03	-0.08	0.14	0.18	-0.10	0.09	-0.11	-0.12	-0.55	-0.31
	(-1.21)	(0.19)	(-0.43)	(0.84)	(1.20)	(-0.56)	(0.59)	(-0.64)	(-0.57)	(-2.29)	(-1.02)
	Panel B: Additional Properties, January 1967-November 2009										
MKT beta	1.03	0.96	0.92	0.88	0.87	0.87	0.87	0.93	0.94	1.05	0.02
	(57.91)	(57.31)	(53.65)	(54.12)	(56.35)	(55.91)	(55.62)	(57.77)	(52.99)	(49.91)	(0.66)
SMB beta	0.60	0.38	0.29	0.28	0.31	0.25	0.29	0.30	0.39	0.55	-0.05
	(24.58)	(16.74)	(12.42)	(12.79)	(14.85)	(11.94)	(13.71)	(13.79)	(16.05)	(19.21)	(-1.23)
HML beta	0.15	0.27	0.31	0.33	0.33	0.30	0.31	0.29	0.21	0.08	-0.07
	(5.69)	(10.89)	(12.11)	(13.38)	(14.47)	(12.84)	(13.10)	(11.92)	(8.07)	(2.57)	(-1.72)
MOM beta	-0.09	-0.09	-0.09	-0.08	-0.06	-0.08	-0.06	-0.05	-0.07	-0.02	0.07
	(-5.24)	(-5.40)	(-5.61)	(-4.85)	(-3.97)	(-5.57)	(-4.05)	(-3.29)	(-4.36)	(-0.95)	(2.66)

factor, MOM. The Fama-French and momentum betas are estimated by regressing the decile excess returns on the returns of the four-factor portfolios. Two of the three Fama-French betas of the 10–1 spread are significantly negative: -0.05 for SMB, and -0.07 for HML. The HML betas indicate that the 10–1 spread has a tilt toward growth stocks. The 10–1 spread's momentum beta is significantly positive (0.07), suggesting some tilt toward past winners.

Alphas

From our previous discussion, we infer that if our recession risk factor is priced, we should observed systematic differences in the mean returns of our DM beta-sorted portfolios. The evidence in table 3 indeed favors the pricing of recession risk. Table 3 reports annualized raw percentage excess returns as well as intercepts (percentage alphas, multiplied by 12) from the regression of monthly excess post-ranking returns of twelve-month equally-weighted portfolios (constructed by sorting U.S. stocks by their pre-ranking, 36-month historical DM recession betas; on the U.S. market factor (MKT, CAPM), three traded Fama-French factors (U.S. market plus size [SMB] and book-to-market [HML]) and four traded factors (three factors plus momentum [MOM]).

Raw returns and alphas are generally increasing across ex-ante DMbeta deciles. All four spread portfolio alphas are positive but insignificant over the full sample (1967-2009) and the two sub-periods (1967-1988 and 1989-2009). For instance, for the full period, all three alphas of the 10–1 spread are positive: the CAPM alpha is 1.27% per year, the Fama-French 3 factor model alpha is 1.93% per year, and the four-factor model alpha is 1.13% per year.(Annual alphas are computed as 12 times the monthly estimates.) However, none of these spread portfolio alphas are significant.

<u>Estimating the Premium: Mutivariate DM beta estimation using all ten portfolios</u>

Further insight on the sign and significance of the recession risk premium comes from its direct estimation using all ten DM recession beta decile portfolios, via the

Table 3. Alphas of value-weighted portfolios of U.S. stocks sorted on historical MD recession betas

This table reports annualized raw percentage excess returns as well as intercepts (percentage alphas, multiplied by 12) from the regression of monthly excess post-ranking returns of twelve-month value-weighted portfolios (constructed by sorting U.S. stocks by their pre-ranking, 36-month historical DM recession betas; on the U.S. market factor (MKT, CAPM), three traded Fama-French factors (U.S. market plus size [SMB] and book-to-market [HML]) and four traded factors (three factors plus momentum [MOM]), The t-statistics are in parentheses.

	Decile Portfolio										
Pre-ranking	1	2	3	4	5	6	7	8	9	10	10-1
	January 1967 - November 2009 (515 months)										
Raw Return	18.91	17.17	16.74	16.71	15.01	15.51	17.25	17.24	18.46	20.25	1.34
	(6.15)	(6.42)	(6.65)	(6.99)	(6.38)	(6.59)	(7.27)	(6.83)	(6.95)	(6.47)	(0.43)
CAPM alpha	7.61	6.59	6.49	6.71	5.08	5.55	7.26	6.92	7.93	8.88	1.27
	(5.72)	(5.90)	(5.95)	(6.36)	(4.93)	(5.56)	(7.14)	(6.76)	(7.05)	(6.48)	(0.91)
Fama-French 3 Factor alpha	5.48	4.08	3.90	4.08	2.40	3.11	4.75	4.54	5.80	7.41	1.93
	(5.93)	(4.69)	(4.38)	(4.84)	(3.04)	(3.84)	(5.90)	(5.51)	(6.38)	(6.98)	(1.37)
Fama-French 4 Factor alpha	6.49	5.07	4.95	4.94	3.07	4.05	5.44	5.11	6.64	7.63	1.13
	(7.05)	(5.85)	(5.59)	(5.86)	(3.86)	(5.03)	(6.70)	(6.13)	(7.26)	(7.02)	(0.80)
	Jan 1967 - Dec 1988 (264 months)										
Raw Return	18.91	17.82	17.52	17.43	15.71	15.86	17.86	18.14	19.03	20.40	1.49
	(4.18)	(4.35)	(4.63)	(4.74)	(4.29)	(4.41)	(4.88)	(4.66)	(4.87)	(4.46)	(0.23)
CAPM alpha	7.01	6.38	6.39	6.43	4.74	4.91	6.83	6.87	7.78	8.49	1.48
	(4.31)	(4.38)	(4.86)	(4.93)	(3.51)	(4.15)	(5.74)	(5.31)	(5.62)	(4.82)	(0.62)
Fama-French 3 Factor alpha	4.13	3.24	3.82	3.50	1.58	2.21	4.41	4.15	5.66	6.87	2.74
	(3.74)	(3.12)	(3.77)	(3.52)	(1.61)	(2.61)	(4.80)	(4.46)	(5.99)	(5.81)	(1.69)
Fama-French 4 Factor alpha	4.59	4.32	5.17	4.54	2.45	3.31	5.37	4.84	5.96	6.59	2.00
	(4.03)	(4.13)	(5.18)	(4.55)	(2.46)	(3.95)	(5.82)	(5.09)	(6.10)	(5.38)	(1.19)
	Jan 1989 - Nov 2009 (251 months)										
Raw Return	18.92	16.48	15.91	15.96	14.28	15.15	16.61	16.29	17.86	20.10	1.19
	(4.55)	(4.83)	(4.84)	(5.27)	(4.90)	(5.05)	(5.56)	(5.13)	(4.99)	(4.72)	(0.20)
CAPM alpha	8.42	7.08	6.84	7.30	5.74	6.50	8.03	7.26	8.24	9.42	1.00
	(3.98)	(4.30)	(3.97)	(4.56)	(3.88)	(4.18)	(5.07)	(4.76)	(4.63)	(4.46)	(0.33)
Fama-French 3 Factor alpha	5.48	4.08	3.90	4.08	2.40	3.11	4.75	4.54	5.80	7.41	1.93
	(5.93)	(4.69)	(4.38)	(4.84)	(3.04)	(3.84)	(5.90)	(5.51)	(6.38)	(6.98)	(1.37)
Fama-French 4 Factor alpha	8.69	6.59	5.81	6.35	4.63	5.75	6.80	6.25	7.74	8.88	0.19
	(6.10)	(5.05)	(4.27)	(5.10)	(4.19)	(4.60)	(5.75)	(4.99)	(5.24)	(5.03)	(0.08)

multivariate GMM procedure we have just described. Table 4 below reports estimates of λ_{DM} and β_i^{DM} for equally-weighted (Panel A) portfolios after accounting for priced sensitivities to the Fama-French three factor ($F_t' = [\text{MKT}, \text{SMB}, \text{HML}]$) model and a four factor

($F_t' = [\text{MKT}, \text{SMB}, \text{HML}, \text{MOM}]$) model[3].

Estimated of the recession risk premiums λ_{DM} in Panel A of Table 4 are always positive and economically and statistically significant. The full-period estimate of λ_{DM} is significantly positive for the equally weighted portfolios under both specifications (three traded factors or four). The sub-period estimates are all positive, and all of them are statistically significant. For example, annualized DM recession risk premiums per average DM recession beta, $\lambda_{DM}\overline{\beta_{\iota,DM}}$, are no less than 4.23% ($t = 7.03$) over the full sample (1967-2009) and as high as 5.95% ($t = 6.25$) over the later sub-period (1989-2009).

The table also reports the GMM estimates of $\lambda_{DM}(\beta_{10}^{DM} - \beta_1^{DM})$, the difference between expected returns on the extreme decile portfolios implied by their recession betas. In the overall period, the annualized estimate of is 2.20% ($t = 1.86$) with three traded factors and 2.28% ($t = 1.79$) with four traded factors. For the later sub-period, remarkably enough, the annualized estimate of $\lambda_{DM}(\beta_{10}^{DM} - \beta_1^{DM})$ reaches a value as high as 4.17 ($t = 2.57$) with three traded factors and 4.15% ($t = 1.79$) with four traded factors.

In summary, we found evidence in Tables 1 and Table 4 that provides additional support to the notion that within U.S. stocks, recession are undesirable and DM betas

[3] Notably, according to Panel A of Table # the over-identifying restriction given by equation $\beta_0 = \beta^{DM}[\lambda_{DM} - E(DM_t)]$ is never rejected by the asymptotic chi-square J -tests at 5% significance levels.

Table 4. DM Recession risk premiums and its contribution to Expected Returns: U.S. stocks

This table reports estimates of annualized percentage of the risk premium (λ_{DM}, multiplied by 12) associated with the DM recession factor for multivariate DM betas (β_i^{DM}) of equally-weighted (Panel A) portfolios constructed by sorting U.S. stocks by their pre-ranking, 36-month historical DM betas (from the lowest [decile 1] to the highest [decile 10]). Specifically, the table reports GMM estimates of λ_{DM} when accounting for the sensitivity of these portfolios' excess returns to the three traded Fama-French factors (U.S. market [MKT], size [SMB], and book-to-market [HML]), four traded factors (Fama-French factors plus momentum [MOM]), over the full sample 1967-2009 and two sub-periods (1967-1988, 1989-2009). We also report estimates of risk premiums per average DM beta ($\lambda_{DM}\overline{\beta_{\iota,DM}}$) and for the 10-1 spread portfolio (going long decile 10 stocks and short decile 1 stocks, $\lambda_{DM}(\beta_{10}^{DM} - \beta_1^{DM})$). Asymptotic t-statistics are in parentheses. J-test is the asymptotic chi-square statistic for the over-identifying restriction in Eq. (8); the corresponding p-values are below.

	1967 - 2009		1967 - 1988		1989 - 2009	
	FF 3 Factor	FF 4 Factor	FF 3 Factor	FF 4 Factor	FF 3 Factor	FF 4 Factor
	Panel A: Equal-weighted portfolios					
λ_{DM}	50.41	46.27	14.51	17.23	29.01	28.39
	(1.65)	(2.01)	(4.84)	(4.83)	(1.69)	(2.07)
$\lambda_{DM}\overline{\beta_{\iota,DM}}$	4.23	5.22	3.56	4.54	4.80	5.95
	(7.03)	(7.94)	(7.67)	(10.67)	(5.43)	(6.25)
$\lambda_{DM}(\beta_{10}^{DM} - \beta_1^{DM})$	2.20	2.28	2.93	2.79	4.17	4.15
	(1.86)	(1.79)	(2.66)	(2.23)	(2.57)	(2.57)
$J - test$	22.51	24.87	22.46	21.77	19.31	17.23
	(0.26)	(0.17)	(0.26)	(0.30)	(0.44)	(0.57)

may be priced such that greater exposure to recession risk is accompanied by higher expected returns.

Financial Recession Factor Portfolio: 10-1 portfolio

Given the evidence we found on the estimation of the recession risk premium via the GMM procedure, we argue that the 10-1 portfolio (being 10 a portfolios of stocks that have a high exposure to recession risk and being 1 a portfolio of stock with low exposure to recession risk) can be used as a traded factor to priced other portfolios.

The traded factor is the value-weighted return on the 10-1 portfolio from a sort on historical recession betas. We argue that this procedure is simpler than sorting on historical betas and it is similarly successful at creating a spread in post-ranking betas. In this final section, we showed that this traded factor that we called $RECF$ for convenience has an increasing positive and significant beta through different asset pricing model, consistent with recession risk being priced.

In Table 5, we report the post ranking $RECF$ betas from the regression of monthly excess post-ranking returns of twelve-month value-weighted portfolios (constructed by sorting U.S. stocks by their pre-ranking, 36-month historical DM recession betas); on the U.S. market factor (MKT, CAPM) plus the recession traded factor ($RECF$), three traded Fama-French factors (U.S. market plus size [SMB] and book-to-market [HML]) plus the recession traded factor ($RECF$), and four traded factors (three factors plus momentum [MOM]) plus the recession traded factor ($RECF$).

CAPM, FF3, FF4 post-ranking RECF beta are increasing and statistically significant across all ten DM beta decile portfolio consistent with recession risk being priced.

Table 5. Post-Ranking Recession Betas of value-weighted portfolios of U.S. stocks sorted on historical MD recession betas

This table reports the post ranking $RECF$ betas from the regression of monthly excess post-ranking returns of twelve-month value-weighted portfolios (constructed by sorting U.S. stocks by their pre-ranking, 36-month historical DM recession betas); on the U.S. market factor (MKT, CAPM) plus the recession traded factor ($RECF$), three traded Fama-French factors (U.S. market plus size [SMB] and book-to-market [HML]) plus the recession traded factor ($RECF$), and four traded factors (three factors plus momentum [MOM]) plus the recession traded factor ($RECF$), The t-statistics are in parentheses.

	Decile Portfolio									
Pre-ranking DM beta	1	2	3	4	5	6	7	8	9	10
	1967-2009									
CAPM Post-ranking RECF beta	-0.427	-0.041	-0.006	-0.035	-0.004	0.069	0.077	0.142	0.230	0.573
	(-18.52)	(-1.47)	(-0.23)	(-1.29)	(-0.14)	(2.64)	(2.98)	(5.49)	(8.35)	(24.88)
FF 3 Post-ranking RECF beta	-0.43	-0.04	-0.01	-0.04	0.00	0.07	0.08	0.14	0.23	0.57
	(-18.52)	(-1.47)	(-0.23)	(-1.29)	(-0.14)	(2.64)	(2.98)	(5.49)	(8.35)	(24.88)
FF 4 Post-ranking RECF beta	-0.41	-0.02	0.01	-0.02	0.01	0.09	0.09	0.15	0.25	0.59
	(-18.19)	(-0.87)	(0.44)	(-0.74)	(0.34)	(3.43)	(3.55)	(6.03)	(9.24)	(25.71)
	1967-1988									
CAPM Post-ranking RECF beta	-0.42	-0.12	-0.15	-0.11	-0.09	-0.02	0.07	0.09	0.17	0.58
	(-7.39)	(-2.11)	(-2.99)	(-2.17)	(-1.82)	(-0.39)	(1.48)	(1.75)	(3.35)	(10.40)
FF 3 Post-ranking RECF beta	-0.47	-0.11	-0.15	-0.08	-0.07	0.00	0.08	0.10	0.15	0.53
	(-15.36)	(-2.84)	(-3.95)	(-2.23)	(-1.88)	(0.03)	(2.45)	(2.88)	(4.29)	(17.53)
FF 4 Post-ranking RECF beta	-0.47	-0.09	-0.13	-0.07	-0.06	0.02	0.10	0.11	0.16	0.53
	(-15.19)	(-2.49)	(-3.57)	(-1.86)	(-1.56)	(0.58)	(3.00)	(3.25)	(4.46)	(17.46)
	1989-2009									
CAPM Post-ranking RECF beta	-0.50	-0.08	0.00	-0.07	-0.03	0.05	0.01	0.10	0.19	0.50
	(-9.57)	(-1.59)	(0.03)	(-1.52)	(-0.71)	(1.08)	(0.17)	(2.36)	(3.81)	(9.59)
FF 3 Post-ranking RECF beta	-0.42	-0.02	0.05	-0.03	0.01	0.08	0.06	0.15	0.25	0.58
	(-12.31)	(-0.50)	(1.15)	(-0.75)	(0.46)	(2.32)	(1.65)	(4.16)	(6.20)	(17.31)
FF 4 Post-ranking RECF beta	-0.39	0.01	0.08	0.00	0.04	0.11	0.08	0.17	0.29	0.61
	(-11.87)	(0.19)	(1.93)	(-0.06)	(1.12)	(3.27)	(2.38)	(4.91)	(7.45)	(18.79)

Conclusions

The CC habit model captures the fundamental idea that consumers become more risk averse as consumption drops during recessions. In this sense, variation across assets in expected returns is driven mainly by variation across assets in covariances with recessions far more than by variation across assets in covariances with consumption growth (Campbell and Cochrane, (1999)). Surprisingly, few articles have tried to estimate and test the Campbell-Cochrane habit utility function on a cross section of stock returns, like for example in the Fama–French 25 size and book-to-market portfolios (Cochrane, 2008).

In this article, we construct an economic and financial "recession factor" using the CC habit formation approach and test the significance of this factor in the cross-section of asset returns, based on factor innovations and portfolios based on factor covariances. We find evidence that the covariance between asset returns and the recession factor drives expected returns.

In other words, fear for recession, measure by innovations to our economic measure DM of recession risk appears to be a state variable that is important for pricing common stocks. We find that expected stock returns are related cross-sectionally to the sensitivities of stock returns to innovations in the economic recession factor. Stocks that are more sensitive economic downturn have substantially higher expected returns, even after we account for exposures to the market return as well as size, value, and momentum factors.

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Chapter 2:

Trading Strategies in Futures Markets

Introduction

Until recently, futures markets were a relatively unknown asset class by both the individual and institutional investor, despite being available for trade in the United States for more than 100 years and even longer in other parts of the world[4]. The reason for this may be that futures market contracts are remarkably different from stocks, in the sense that they are short-maturity derivative claims on real assets, not claims on long-lived corporations; and possibly because of the lack of easily futures markets return data (Gorton and Rouwenhorst, 2006).

However, in recent times, individual and institutional investors are turning to futures markets to trade. Moreover, recent academic research has claimed "equity-like" returns to portfolios of commodity futures while also touting the diversification benefits relative to traditional asset classes[5] (Gorton and Rouwenhorst, 2006; Erb and Harvey, 2006). Markets participants also find in futures a first-rate instrument to hedge against inflation. Futures also offer leverage and are not subject to short-selling restrictions prevalent in the equity markets. Moreover, the nearby contracts are usually very liquid and transaction costs are low compared to the stocks markets trade. These make futures good candidates for tactical and strategic asset allocation (Wang and Yu, 2004; Erb and Harvey, 2006) with new implications for futures market efficiency and for futures market participants' trading strategies.

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[4] For example, Japanese rice futures, which originated the modern futures markets, were traded in Osaka starting in the early 18th century (see Anderson, Hamori, and Hamori 2001).

[5] However, recent research by Daskalaki and Skiadopoulos (2010) shows that this widely-touted diversification role of commodities does not necessarily hold up out-of-sample.

This study investigates whether the profitable momentum portfolio strategy (of buying past winners and selling past losers) and the long-term contrarian portfolio strategy (of buying past losers and selling past winners) identified in equity markets by Jegadeesh and Titman (1993, 2001) and De Bondt and Thaler (1985) are present in a cross-section of broad futures markets. Our article builds on the research of Wang and Yu, (2004) and Erb and Harvey (2006). The authors find strong evidence of futures return reversals over the 1-week horizon. Specifically, they find that a contrarian strategy of buying past losers and selling past winners gives rise to an average return of 0.31% per week (16.12% per annum). Erb and Harvey's article find evidence that a momentum strategy of buying past winners and selling past losers with a 12-month ranking period and a 1-month holding period is profitable in futures markets achieving an attractive excess return of 10.8% per year.

In particular, this paper looks at the performance of 16 momentum strategies in futures markets for four ranking periods (4, 6, 9 and 12 months) and four holding periods (1, 2, 3, and 4 months). We find that the winner portfolios typically outperform the loser portfolios over holding periods that range from 1 to 4 months and this pattern holds for each of our formation periods. Across the 16 strategies that are profitable, one could make a profit of an average return of 33.63% a year by consistently buying the best performing futures and selling the worst performing ones. We also find evidence of a contrarian strategy in which past winners turn into losers over ranking and holding periods that range from 1 to 5 years. The average returns of the past winner portfolios range from -3.92% to -0.94% a year while the average returns of the past loser portfolios range from 6.78% to 16.07%.

The remainder of this paper is organized as follows. Section 2 describes the data set and shows summary descriptive statistics. Section 3 summarizes the methodology used to construct momentum and contrarian portfolios. Section 4 discusses the results from the momentum strategies. Section 5 highlights the results of the contrarian strategies. Finally, section 6 highlights the most important finding in our article and delineates further guidelines for future research.

2 Data Description

In this article, we analyze monthly settlement prices for 43 US futures market contracts over the period January 1970-June 2008. These data were obtained from Price-Data Corporation. To avoid survivorship bias, we include contracts that started trading after January 1970 or were delisted before June 2008. In consequence, the total sample size ranges from a low of 12 contracts over the period April 1970-November 1973 to a peak of 43 contracts over the period January 1999-September 2003.

The composition of our sample is as follows: we consider eight currencies futures (Australian Dollar, British Pound, Brazilian Real, Canadian Dollar, Dollar Index, Euro Currency, Japanese Yen, Swiss Franc), three energies futures (Crude Oil, Heating Oil, and Natural Gas), eight financials futures (Eurodollars, EuroYen, Fed. Funds, Five Year Notes, Muni Bonds, Treasury Bills, Ten Year Notes, Thirty Year Bonds), five foods futures (Cocoa, Orange Juice, Coffee, Rough Rice, Sugar), eight grains futures (Soybean Oil, Corn, Kansas City Wheat, Minnesota Wheat, Oats, Soybeans, Soybean Meal, Wheat), seven metal/fiber futures (Cotton #2, Gold, High Grade Copper, Lumber, Palladium, Platinum, Silver), and lastly, four meat futures (Feeder Cattle, Live Cattle, Lean Hogs, Pork Bellies). One word of caution about our sample is worth mentioning. We do not include contracts that are traded in international markets such as London futures, Sydney futures, Tokyo futures and Winnipeg futures markets. It is noted that excluding these contracts might introduces a sample selection bias.

Following the tradition in the futures markets' literature, we compute monthly futures returns as the change in the logarithms of the settlement prices. Continuous series of futures returns are created for each futures contract, for both the first and the second nearest-to-maturity contracts. Because individual futures contracts have a finite life defined by the contractual delivery date, an investor must sell a maturing contract and buy a yet-to-mature contract. This process is referred to as ”rolling” a futures position. Therefore, these return series are created by using a rollover strategy. The procedure is as follows. First, we collect the futures prices on all nearest and second nearest contracts. We hold the first nearby contract up to one month before maturity. At the end of that month, we roll our position over to the second nearest contract and hold that contract up to one month prior to maturity. The procedure is then rolled forward to the next set of nearest and second nearest contracts when a new sequence of futures returns is computed[6].

The article also tests the sensitivity of the results to the day of the month employed to compute futures returns. Therefore, we not only calculated monthly returns by picking the settlement price of the first trading day for each month as in Fama and French (1987) but we also calculate returns based on the price of the last trading day of the month as in Erb and Campbell (2006). Moreover, to ensure that the results are not driven by weekend effect we calculate returns based on the second Wednesday prices of each month (See Table 1). This exercise indicates that the day of the month chosen to calculate the returns do not alter our results. To see why this is the case, notice that the summary statistics presented in Table 1 are all similar to the one presented in Table 2.

Table 1 Sensitivity Analysis for Futures Returns Construction

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[6] Ma, Mercer, and Walker (1992) show that the choice of the rollover date can have unpredictable effects on the results of empirical studies. They compare different methods to rollover futures and demonstrate that important biases are generated from its selection. However, recent research by Carchano and Pardo (2009) indicate that the choice of the criterion to link the maturities does not matter for the construction of continuous series of returns.

Returns are calculated from monthly data for the period January 1970 to June 2008. Mean returns and standard deviations are annualized and are in percentages. Monthly returns are calculated by picking the settlement price of the second Wednesday of the month, the first trading day and last trading day of each month.

	Average			Std. Dev.		
	2nd Wed	First Trading Day	Last Trading Day	2nd Wed	First Trading Day	Last Trading Day
Foods						
Cocoa	3.42	3.17	3.37	30.00	30.58	30.26
Orange Juice	2.34	2.36	2.01	31.32	31.04	31.22
Coffee	2.15	1.98	2.14	35.78	37.83	37.61
Rough Rice	7.17	7.25	7.02	31.50	30.19	30.49
Sugar	3.22	3.24	2.94	43.11	41.84	40.73
Grains				0.00	0.00	0.00
Soybean Oil	5.09	5.14	4.97	31.99	32.09	32.66
Corn	4.24	4.33	4.27	24.81	25.87	24.77
Kansas City Wheat	2.49	2.48	2.59	23.35	21.49	21.79
Minnesota Wheat	2.18	2.17	2.19	24.15	22.38	22.87
Oats	5.05	4.72	4.91	28.76	31.86	31.63
Soybeans	4.50	4.55	4.47	26.45	29.43	28.19
Soybean Meal	4.04	3.89	3.95	28.18	29.63	33.87
Wheat	4.42	4.47	4.44	27.34	26.18	26.53
Metals/Fiber				0.00	0.00	0.00
Cotton	2.72	2.46	2.57	30.17	28.52	28.74
Gold	4.82	4.80	4.80	20.65	19.16	19.13
High Grade Copper	4.47	4.28	4.39	25.62	26.46	26.12
Lumber	1.60	1.82	1.88	29.05	29.50	29.57
Palladium	7.00	7.06	6.59	34.91	36.03	35.90
Platinum	6.72	6.68	6.65	26.70	28.48	27.17
Silver	5.73	5.80	5.66	33.86	32.08	31.90
Meats				0.00	0.00	0.00
Feeder Cattle	1.99	1.93	2.21	18.44	18.12	18.09
Live Cattle	2.99	3.25	3.16	21.29	20.26	20.22

Lean Hogs	2.76	2.64	2.76	31.52	32.83	32.02
Pork Bellies	1.45	1.37	1.32	44.26	41.02	42.10
Energies						
Crude Oil	5.70	5.98	6.00	32.12	32.12	32.53
Heating Oil	6.36	6.36	5.80	30.90	33.06	33.04
Natural Gas	10.54	11.53	11.19	54.62	56.16	57.96
Financials				0.00	0.00	0.00
Eurodollars	0.57	0.54	0.48	1.95	1.98	1.94
EuroYen	0.32	0.31	0.32	0.69	0.68	119.83
Fed. Funds	0.34	0.35	0.33	1.00	0.93	0.96
Five Year Notes	0.67	0.66	0.64	4.75	4.92	4.82
Muni Bonds	0.99	1.00	1.04	10.76	10.05	10.04
Treasury Bills	0.15	0.16	0.15	2.88	2.44	2.45
Ten Year Notes	1.77	1.74	1.56	7.49	7.41	7.24
Thirty Year Bonds	1.03	1.02	0.97	14.78	14.28	14.07
Currencies						
Australian Dollar	1.68	1.85	1.79	9.64	10.10	9.95
British Pound	-0.57	-0.49	-0.45	10.51	10.40	10.48
Brazilian Real	-4.25	-4.11	-4.00	45.51	46.53	48.95
Canadian Dollar	0.07	0.07	0.11	5.32	5.77	5.75
Dollar Index	-2.37	-2.49	-2.37	8.73	8.87	8.60
Euro Currency	3.02	2.90	3.38	9.62	9.54	8.96
Japanese Yen	3.29	3.30	3.22	11.75	12.22	11.87
Swiss Franc	2.44	2.60	2.47	12.09	12.53	12.40

Table 2 presents summary statistics for monthly futures returns over the sample period for the nearest-to-maturity series for all contracts. Table 2 shows a positive unconditional mean return for all except the British Pound, Brazilian Real and Dollar Index futures markets. The return is insignificant. This suggests that a simple buy-and-hold strategy is not likely to be profitable in most futures markets. Without exception, the t-values reported in column 3 of Table 2, show that for most futures contracts, the average futures return is not significantly different from zero. Bessembinder (1992), and

Bessembinder and Seguin (1993) use a sample period that only partially overlaps with our sample period and report similar statistics for these categories of futures contracts. However, they find that mean returns on agricultural and mineral futures are comparable in (absolute) size with the mean returns on financial and currency futures. We find similar results in our sample. For instance, mean returns on foods, grains, metals/fiber, meat and energies futures are larger than the mean returns on financial and currency futures. As expected, standard deviations for foods, grains, metals/fiber, meat and energies futures returns are also somewhat larger than for financial futures.

Table 2 Summary Statistics for Futures Returns

Returns are calculated from monthly data for the period January 1970 to June 2008. Mean returns and standard deviations are annualized and are in percentages

Contract Name	Mean	Std. Dev.	t-value
Currencies			
Australian Dollar	1.68	39.03	0.69
British Pound	-0.57	43.16	-0.26
Brazilian Real	-4.25	339.87	-0.15
Canadian Dollar	0.07	20.07	0.07
Dollar Index	-2.37	34.79	-1.12
Euro Currency	3.02	38.90	0.82
Japanese Yen	3.29	49.24	1.30
Swiss Franc	2.44	50.96	0.96
Financials			
Eurodollars	0.57	6.95	1.45
EuroYen	0.32	2.42	1.89
Fed. Funds	0.34	3.50	1.48
Five Year Notes	0.67	17.74	0.58
Muni Bonds	0.99	44.35	0.35
Treasury Bills	0.15	10.46	0.27
Ten Year Notes	1.77	29.28	1.02

Thirty Year Bonds	1.03	65.12	0.30
Energies			
Crude Oil	5.70	189.83	0.52
Heating Oil	6.36	178.82	0.67
Natural Gas	10.54	479.49	0.32
Foods			
Cocoa	3.42	170.89	0.41
Orange Juice	2.34	182.55	0.28
Coffee	2.15	225.31	0.19
Rough Rice	7.17	184.13	0.63
Sugar	3.22	308.52	0.22
Grains			
Soybean Oil	5.09	188.63	0.58
Corn	4.24	129.34	0.70
Kansas City Wheat	2.49	118.72	0.41
Minnesota Wheat	2.18	124.49	0.32
Oats	5.05	160.42	0.68
Soybeans	4.50	141.82	0.68
Soybean Meal	4.04	155.62	0.56
Wheat	4.42	148.80	0.64
Metals/Fiber			
Cotton	2.72	172.42	0.34
Gold	4.82	100.36	0.96
High Grade Copper	4.47	135.45	0.71
Lumber	1.60	162.86	0.20
Palladium	7.00	216.53	0.63
Platinum	6.72	143.77	1.00
Silver	5.73	206.18	0.60
Meats			
Feeder Cattle	1.99	86.32	0.47
Live Cattle	2.99	104.57	0.61
Lean Hogs	2.76	184.31	0.32
Pork Bellies	1.45	323.28	0.10

3 Methodology

This paper evaluates 32 trading strategies. In particular, we focus on 16 short-term momentum strategies with four ranking periods (4, 6, 9, and 12 months) and four holding periods (1, 2, 3, and 4 months) and in 16 long-term contrarian strategies with four ranking periods (12, 24, 36 and 60 months) and four holding periods[7] (12, 24, 36 and 60 months).

Futures contracts are sorted at the end of each month into deciles based on their average return over the previous J months (ranking period). The decision to form deciles was based our desire to enhance the dispersion of returns between the best and worst performing futures and thus the profitability of the strategies. By adopting this approach, our cross section return gets smaller as the risk diversification decreases. Wang and Yu (2004) find evidence suggesting that trading activity enhances short-term contrarian profits in futures markets. Therefore, the futures contracts in each of the deciles are value weighted by adopting a weighting scheme that assigns higher weights to the contracts with higher open interests.

The performance of both the top and bottom deciles is monitored over the subsequent K months holding period over which no rebalancing is made. We call the resulting strategy the J-K momentum or contrarian strategy. Following the traditional momentum literature (Moskowitz and Grinblatt, 1999 and Jegadeesh and Titman, 2001), we form overlapping winner and loser portfolios. Taking, as an example, the 6-3 momentum strategy, the winner portfolio in, say, November is formed by equally weighting the top 3 deciles portfolios that were formed at the end of August, September and October. The same mechanics applies to the loser portfolio. Its return is equal to

[7] The choice of the formation and holding periods is arbitrary. Wang and Yu (2004) study focused on the 1-week horizon for the contrarian strategy. Badrinath et al. (1995) and Chordia and Swaminathan (2000) suggest that it may take longer for some asset prices to revert after under/outperforming; therefore, we consider the formation period up to 12 months and the holding period up to 4 months. This seems appropriate given that futures trading usually concentrates on contracts that typically mature within two or three months.

the average return in November of the 3 bottom deciles that were formed at the end of August, September and October. The return of the momentum (contrarian) strategy is then simply defined as the difference in the November returns of the winner (loser) and loser (winner) portfolios. The procedure is rolled over to the next month, where another set of winners, losers, momentum and contrarian portfolios is formed. Since the October winner and loser contribute towards only a third of the November momentum profits, it is realistic to assume that the momentum profits are not driven by bid-ask bounce. Therefore, following Moskowitz and Grinblatt (1999), we chose not to skip a month between the ranking and holding periods.

4 Momentum Strategies

In this section we examine whether future returns are predictable based on past returns over short horizons in futures markets by showing the results of our momentum strategies. We test 16 short-term momentum trading strategies with four ranking periods (4, 6, 9 and 12 months) and four holding periods (1, 2, 3, and 4 months). Table 3 presents summary statistics of returns for these short-term momentum strategies where the rows represent the ranking periods in which the portfolios cumulative returns were calculated and the columns the holding periods. For example, the first row and column present the average return for a portfolio of a relative strength strategy based on 12 month lagged returns and one month holding period.

Table 3 Summary Statistics of Returns of Relative Strength Portfolios

The mean and standard deviation are annualized. The reward-to-risk ratio is measured as the ratio of the annualized mean to the annualized standard deviation. The p-values for the significance of the mean are in parentheses. Our definition of returns assumes that we hold contracts up to one month before maturity, at which date the position is rolled over to the second nearest contract and held up to one month prior to maturity. Futures prices are collected at a monthly frequency, in particular for the second Wednesday of each month to avoid the weekend effect.

	1-Month Holding Period			2-Month Holding Period			3-Month Holding Period			4-Month Holding Period		
Portfolios based on	**Sell Losers**	**Buy Winners**	**Buy-Sell**	**Sell Losers**	**Buy Winners**	**Buy-Sell**	**Sell Losers**	**Buy Winners**	**Buy-Sell**	**Sell Losers**	**Buy Winners**	**Buy-Sell**
12 months lagged returns												
Mean	-13.10	29.88	49.03	-7.32	20.63	29.70	-4.00	16.95	21.55	-0.03	12.88	12.77
p-value	(0.00)	(0.00)	(0.00)	(0.11)	(0.01)	(0.00)	(0.38)	(0.01)	(0.01)	(0.99)	(0.04)	(0.09)
Std	30.42	52.79	60.63	29.77	42.36	50.90	29.06	38.36	47.26	28.33	36.09	44.43
Sharpe Ratio	-0.431	0.566	0.809	-0.246	0.487	0.583	-0.138	0.442	0.456	-0.001	0.357	0.287
9 months lagged returns												
Mean	-13.76	28.44	47.67	-4.36	17.55	22.44	-1.46	15.41	16.12	0.13	13.27	12.12
p-value	(0.00)	(0.00)	(0.00)	(0.32)	(0.01)	(0.01)	(0.74)	(0.01)	(0.03)	(0.98)	(0.02)	(0.08)
Std	28.76	44.72	52.09	27.75	40.71	47.27	27.61	36.38	43.06	27.30	34.13	41.23
Sharpe Ratio	-0.4784	0.6359	0.9151	-0.1570	0.4312	0.4748	-0.0529	0.4236	0.3743	0.0047	0.3890	0.2941
6 months lagged returns												
Mean	-21.72	30.37	65.34	-11.88	18.73	34.33	-6.18	13.33	20.06	-2.50	10.10	11.81

p-value	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.14)	(0.04)	(0.01)	(0.54)	(0.08)	(0.07)
Std	29.81	57.14	62.58	28.23	43.39	48.46	26.95	38.19	43.58	26.04	34.54	39.22
Sharpe Ratio	-0.7287	0.5316	1.0440	-0.4210	0.4316	0.7084	-0.2292	0.3490	0.4604	-0.0959	0.2924	0.3011
4 months lagged returns												
Mean	-28.71	41.11	96.08	-16.77	25.72	49.92	-10.27	16.72	28.72	-5.66	14.91	20.52
p-value	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.03)	(0.00)	(0.15)	(0.01)	(0.00)
Std	30.53	64.69	68.82	27.27	52.79	56.51	26.49	44.62	47.61	25.60	33.96	37.30
Sharpe Ratio	-0.9403	0.6354	1.3960	-0.6149	0.4872	0.8834	-0.3877	0.3746	0.6032	-0.2211	0.4392	0.5499

It is clear from Table 3 that the winner portfolios typically outperform the loser portfolios over holding periods that range from 1 to 4 months. Note that this pattern holds for each of our formation periods. Note that for 12 out of 16 strategies the difference in returns between the winner and the loser portfolios is positive and significant at the 1% level. The other four strategies give us a positive average return and are still significant at the 5% level. Across the 16 strategies that are profitable, one could earn an average return of 33.63% a year by consistently buying the best performing futures contracts and selling the worst performing ones. The results in Table 3 are consistent with Erb and Harvey (2006) who observe that a 12-1 momentum strategy is profitable in futures markets. Our results are also in line with the well-known results of Jegadeesh and Titman (1993, 2001) who show that stocks that perform the best (worst) over a 3 to 12 months period tend to continue to perform well (poorly) over the subsequent 3 to 12 months.

We observe that in 10 out of the 16 strategies that are profitable, the loser portfolios always earn negative and significant average return that range from a low of -0.03% (for the 12-4 strategy) to a high of -28.71% (for the 4-1 strategy). The data from the 16 winner portfolios is significant both in economic and statistical terms. The winner portfolios offer average returns that can range from a low of 10.10% (for the 6-4 strategy) to a high of 41.11% (for the 4-1 strategy). According to our results and within the frame of our 16 trading strategies we can conclude that price continuation in futures markets is mainly driven by the winners.

We also report in Table 3 the annualized standard deviations and the Sharpe's reward-to-risk ratios of the strategies given the possibility that the momentum strategies might pay off as a compensation for risk. As we would expect, the most profitable strategies rank among the most risky. To see why this is the case, notice that the 4-1 momentum strategy with an average returns of 96.08% offers the highest average returns and, with a standard deviation of 68.82%, it is also the most volatile. On the other hand, any trading strategy that combines any of the proposed rankings periods (12, 9, 6, or 4) with 4-month holdings period momentum strategy falls among the lowest level of risk strategies (between 37.30% and 44.43%), subsequently, it gives the lowest average return (between 11.81% and 20.52%).

However, two unexpected result are worth mentioning. The 6-1 and 4-1 profitable momentum strategies in Table 3 had reward-to-risk ratios greater than one, which indicates that the return is greater than or proportional to the risk the investor incurred to earn that return. A negative Sharpe ratio would indicate that a risk-less asset would perform better than the security being analyzed. Over the same period, a long-only portfolio that equally weights the 43 futures contracts we considered in this study earned 5.09% a year with a Sharpe ratio of 0.001. We also note that over the same period, the S&P500 composite index had earned a 1.18% a year with a Sharpe ratio of 0.1325. Overall, this indicates that momentum strategies perform better on a risk-adjusted basis than passive long-only strategies in equity and futures markets.

5 Contrarian Strategies

This section presents the summary statistics of returns of long-term contrarian strategies in futures markets. In particular, it analyzes 16 long-term contrarian strategies with four ranking periods (12, 24, 36 and 60 months) and four holding periods (12, 24, 36 and 60 months). Table 4 reports summary statistics of returns of long-term contrarian strategies. A contrarian strategy states that the losers (winners) in the ranking period will turn into winners (losers) in the holding period. Similarly, the winners in the ranking period will turn into losers in the holding period. Consequently and consistent with DeBondt and Thaler (1985), a contrarian strategy that deliberately buys the long-term underpriced losers and sells the long-term overpriced winners turn out to be lucrative

The results in Table 4 indicate that the systematic rebalancing of futures contracts portfolios using a contrarian approach is a source of abnormal returns in futures markets. There is evidence that past winners turn into losers over ranking and holding periods that range from 1 to 5 years. The average returns of the past winner portfolios range from -3.92% to -0.94% a year while the average returns of the past loser portfolios range from 6.78% to 16.07%. As a result, all of the contrarian strategies are lucrative.

The findings have other notable aspects. First, the contrarian pattern identified in stock markets over long-term horizons by De Bondt and Thaler (1985) is present in futures markets and they are consistent with the overreaction hypothesis. Second, the overreaction effect is asymmetric; it is much larger for losers than for winners. Finally, the overreaction phenomenon mostly occurs during the second year of the test period, if we exclude the (J, 1) contrarian strategies.

It would be interesting to investigate in future research whether the profits remain significant after corrections for plausible transaction costs in futures trading, and whether imperfections in market microstructure like bid-ask spread and nonsynchronous trading have a non-trivial effects in our futures markets' sample. Granted that transaction costs in futures markets range from 0.0004% to 0.033% (Locke and Venkatesh, 1997), which is much less than the conservative 0.5% estimate of Jegadeesh and Titman (1993) for the equity market, we do not expect that including transaction costs would affect our results in a significant way.

Table 4 Summary Statistics for Returns of Contrarian Portfolios

The mean and standard deviation are annualized. The reward-to-risk ratio is measured as the ratio of the annualized mean to the annualized standard deviation. The p-values for the significance of the mean are in parentheses. Our definition of returns assumes that we hold contracts up to one month before maturity, at which date the position is rolled over to the second nearest contract and held up to one month prior to maturity. Futures prices are collected at a monthly frequency, in particular for the second Wednesday of each month to avoid the weekend effect.

	1-Year Holding Period			2-Year Holding Period			3-Year Holding Period			5-Year Holding Period		
Portfolios based on	**Sell Winners**	**Buy Losers**	**Buy-Sell**	**Sell Winners**	**Buy Losers**	**Buy-Sell**	**Sell Winners**	**Buy Losers**	**Buy-Sell**	**Sell Winners**	**Buy Losers**	**Buy-Sell**
5 years lagged returns												
Mean	-3.17	16.07	20.80	-0.98	12.50	14.66	-1.01	9.45	11.88	1.76	6.78	6.00
p-value	(0.45)	(0.00)	(0.00)	(0.80)	(0.01)	(0.01)	(0.78)	(0.04)	(0.02)	(0.61)	(0.12)	(0.20)
Std	24.93	28.35	33.69	22.92	27.67	31.13	21.43	26.46	28.80	20.63	25.29	26.78
Sharpe Ratio	-0.127	0.567	0.618	-0.043	0.452	0.471	-0.047	0.357	0.412	0.085	0.268	0.224
3 years lagged returns												
Mean	-0.94	13.57	15.67	0.77	13.13	13.40	1.87	10.44	9.69	3.70	7.11	4.16
p-value	(0.82)	(0.00)	(0.00)	(0.84)	(0.00)	(0.00)	(0.60)	(0.02)	(0.03)	(0.29)	(0.07)	(0.23)
Std	24.65	27.33	30.84	22.89	25.73	26.71	21.77	26.03	25.67	20.99	23.40	20.86

Sharpe Ratio	-0.0381	0.4966	0.5082	0.0336	0.5103	0.5015	0.0857	0.4011	0.3775	0.1762	0.3041	0.1995
2 years lagged returns												
Mean	-3.92	12.57	17.80	-1.09	14.44	16.31	0.68	12.53	12.48	2.58	9.90	7.52
p-value	(0.37)	(0.01)	(0.00)	(0.77)	(0.00)	(0.00)	(0.85)	(0.00)	(0.00)	(0.46)	(0.01)	(0.04)
Std	27.54	27.81	34.32	23.47	25.11	27.04	22.24	24.03	23.72	21.74	23.27	21.67
Sharpe Ratio	-0.1423	0.4520	0.5186	-0.0465	0.5752	0.6034	0.0304	0.5213	0.5263	0.1184	0.4254	0.3469
1 years lagged returns												
Mean	5.83	6.13	1.46	3.07	8.91	7.56	4.72	9.18	5.62	4.63	8.36	4.79
p-value	(0.20)	(0.15)	(0.78)	(0.43)	(0.02)	(0.06)	(0.19)	(0.01)	(0.09)	(0.16)	(0.02)	(0.09)
Std	27.86	26.21	31.93	23.90	23.71	23.75	22.05	21.94	20.12	20.20	21.81	17.09
Sharpe Ratio	0.2092	0.2338	0.0458	0.1283	0.3760	0.3183	0.2142	0.4183	0.2795	0.2292	0.3831	0.2805

6 Conclusions

In this article, we examine whether futures markets returns are predictable based on past returns over short and long horizons. In particular, we look at the performance of 16 momentum strategies in a cross-section of broad futures markets for four ranking periods (4, 6, 9 and 12 months) and four holding periods (1, 2, 3, and 4 months). Our results show that the winner portfolios typically outperform the loser portfolios over holding periods that range from 1 to 4 months. We document that this pattern holds for each of our formation periods. Across the 16 strategies that are profitable, one could earn an average return of 33.63% a year by consistently buying the best performing futures and selling the worst performing ones.

We also find evidence that past winners turn into losers over ranking and holding periods that range from 1 to 5 years. The average returns of the past winner portfolios range from -3.92% to -0.94% a year while the average returns of the past loser portfolios range from 6.78% to 16.07%. As a result, all of the contrarian strategies are profitable.

Overall, our article indicates that relative-strength and contrarian strategies perform better on a risk-adjusted basis than passive long-only strategies in equity and futures markets, making futures markets contracts attractive candidates to be included in well-diversified portfolios. Further, since arbitrage strategies are more readily available than in equity markets due to the low cost and high liquidity of futures trading, these results have significant implications for academics in terms of market efficiency and for practitioners in terms practical trading strategies and asset allocation.

A question left for further research is related to the role of institutional investors in futures markets. An interesting exercise could be to test whether the momentum profits have decreased recently due to a rising interest of institutional investors in futures markets.

Finally, it would be interesting to study also whether the profits remain significant after corrections for plausible transaction costs in futures trading, and second whether imperfections in market microstructure like bid-ask spread and non-synchronous trading have a non-trivial effects in our futures markets' sample.

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Chapter 3

Information Sharing Networks in the Banking Industry

1 Introduction

The literature has long stressed that banks face "adverse selection" or "moral hazard" problems in its lending activity. Adverse selection arises when some information about the borrowers' characteristics (i.e. credit applicants' projects riskiness) remain hidden to the lender and can lead to an inefficient allocation of credit, for instance to its rationing (e.g.**?**). Moreover, after credit is granted moral hazard arises instead from the lender's inability to observe borrower's actions (i.e. lack of effort in ensuring the project's success or attempt to default partly on the loan by renegotiating it) that affect the probability of repayment.

To a certain extent, these adverse selection and moral hazard problems can be alleviated if the borrower can pledge some collateral, or if he owns a considerable equity stake in the project or by keeping a good reputation in the business community. Unfortunately, many credit applicants, for instance, young and small firms, typically lack sufficient collateral and equity capital and have a short length of credit history.

Screening credit applications may help to reduce the adverse selection problem and monitoring borrowers may help to ease the moral hazard problem. The production of information is costly and the incentives to spend on information production may be reduced by the free rider problem. For instance, while the outcome of the screening test may not be observable by third parties, competitor banks can still extract information about the screened entrepreneurs by simply observing whether the bank extends or denies the loan.

A cheaper and more effective way to acquire information is by exchanging it with other lenders. In practice, we observe a considerable exchange of information among lenders.

In many countries lenders communicate data concerning their customers' creditworthiness to one another or can access databases that help them assess credit applicants. Most of the times, this information exchange takes place via formal mechanisms. Some of these are voluntary, while others are imposed by regulation.

"Credit bureaus" are typical voluntary mechanisms, which operate on the principle of reciprocity, collecting, filing and distributing the information supplied voluntarily by their members. The incentive members have to truthfully reveal information is enforced invariably by threatening deviants that they will be excluded from access to the common data base. Some bureaus are profit-oriented ventures created at the initiative of entrepreneurs; others are set up by coalitions of lenders as cooperative arrangements [1].

Public credit registers, instead, are databases created by public authorities and managed by central banks. Their data are compulsorily reported by lenders, who then obtain a return flow of data for use in their lending decisions.

In many developing countries, entrepreneurs complained that formal lenders request their loans to be assisted by collateral whose value often greatly surpasses the value of the loan. Moreover, in some cases, lenders exert no effort at all to learn the intrinsic value of the cash flows that can be generated by the project they are financing. The availability of more readily usable information, together with the acquaintance with credit scoring techniques, may contribute to a shift in their lending strategy, as highlighted by **?**. The availability of better mechanism for sharing information may lead banks to move somewhat from a collateral-based lending policy to an information-based one improving the efficiency of financial intermediaries.

Sharing credit information finds a limit in the set of legal provisions designed to protect individual privacy. Such provisions differ widely both within Europe and between the

[1] Also credit rating agencies, such as Duns & Bradstreet in the US, can be seen as a voluntary information sharing mechanisms, insofar as they draw a large portion of their data from lenders and suppliers, who in return obtain preferential access to their data.

US and European countries, and these differences appear to have had profound effects on the development of credit information systems (see **?**). For instance, Frances strict safeguards for consumer privacy are so strong that regulation has impeded the emergence of private credit bureaus. In medium-protection countries as the United States, data can be accessed only for an "admissible purpose", essentially the granting of credit. There are low-protection consumer privacy countries, such as Argentina, where virtually anyone can is granted access to all debtors data not considering the purpose of the investigation.

In many countries lenders communicate data concerning their customers creditworthiness to one another or can access databases that help them assess credit applicants. Often lenders agree to exchange of information spontaneously, via information brokers such as credit bureaus. In other cases they are obliged to do so by the authorities via public credit registers. However, the type, quality, and quantity of data available, and information-sharing mechanism, vary greatly from country to country.

This article studies in a normative way style the theoretical foundations that lenders have to share credit information about borrowers or project's quality. The question of which is the best mechanism or network architecture to share information may have important implication for the regulation of the financial system, given the important effect that financial systems have in the economy.

We construct a model in which banks operate in different market structures following the model by **?**. In this setting information production is the main role played by banks. In particular, I assume that banks have access to a screening technology that, at a cost, allows them to discriminate among high and low quality investments projects (i.e. different types of borrowers). However, given the free-riding problem associated with information production, I set out the model in a network architecture which allows the study of R&D alliances as a means to internalize spillovers.

Using different network structures, I model different ways by which banks may be connected to share information. The novelty of the article is that I model the banking industry within a network framework that provide us with some useful insights on: (1) how bank interconnections affect the level of effort (i.e. investment in information technologies) that individual financial institutions devote to screen the quality of new investment projects. (2) How the degree to which banks are connected to each other through bilateral exposures may affect its marginal cost of producing information about the creditworthiness of the borrowers. (3) How bank interconnections affect the level of profit of the individual financial institutions.

The model gives an answer to what is the optimal number of credit sharing information alliances individual banks should have to maximize expected profits, taking into account the different market structure in which they interact. I find that if banks operate in independent markets, then it is optimal that each bank shares credit information with all the other banks. This is in line with the tendency of credit bureaus - that were set up originally by small coalitions of lenders as cooperative arrangements - to be totally integrated in one big credit agency.

Other finding is that in homogeneous loan market, where banks compete a la Cournot (banks operate within an oligopolistic industry), banks profits are maximized at an intermediate level of sharing credit information. This result also may add an alternative explanation why we observe syndicated loans [2] even in countries in which formal sharing information systems are well established. Syndicated loans allow the sharing of credit risk between various financial institutions without the disclosure and marketing burden that bond issuers face (in other words, they allow the partial elimination of the adverse selection and moral hazard cost of originating the loan for the bank loans portfolio).

[2] A syndicated loan is a credit granted by a group of lenders, typically commercial banks, to a borrower. Every syndicate member has a separate claim on the debtor, although there is a single loan agreement contract. The creditors can be divided into two groups. The first group consists of senior syndicate members and is led by one or several lenders, typically acting as mandated arrangers, arrangers, lead managers or agents. The second group, the junior banks may vary their number and identity according to the size, complexity and pricing of the loan as well as the willingness of the borrower to increase the range of its banking relationships.

Leading banks may have several reasons for arranging a syndication. It can be a means of avoiding excessive single-name exposure, in compliance with regulatory limits on risk concentration, while maintaining a relationship with the borrower. For junior banks, participating in a syndicated loan may be advantageous for several reasons. These banks may be motivated by a lack of origination capability in certain types of transactions, geographical areas or industrial sectors, or indeed a desire to cut down on origination costs. While junior participating banks typically earn just a margin and no fees, they may also hope that in return for their involvement, the client will reward them by getting loans directly from them in the future, or with more profitable business, such as treasury management, corporate finance or advisory work. A new transaction with someone with whom one has a history of prior relationships or who has ties with others to whom one is also connected poses far lower transaction and coordination costs than might be expected within a more traditional analysis.

This research may be important to evaluate the economic effects of information sharing systems obtaining directions for the design of credit information systems, especially in developing countries, in which, the role of informal lending and informal information sharing is much larger than in developed economies.

The rest of the article is organized as follows. In section 2, we introduce some network terminology and describe the model. Section 3, we use the model to see the effect of strategic alliances on banks that operates in a oligopolistic environment. Section 4 concludes.

2 The model

We consider a three-stage game. At stage one, banks form pair-wise collaboration links. For the sake of simplicity, forming links is costless. The purpose of these connections in the banking industry is sharing knowledge about a cost-reducing screening technology that allows them to discriminate the quality of investment projects or the creditworthiness of the borrower. At stage two, the R&D (information sharing) alliances are set up and banks choose their individual level of R&D expenditure (in order to increase the quality of the screening process) that maximizes their expected payoffs. The R&D efforts, along with the networks of collaboration, define the cost structure of the banks. Finally, at stage three, banks operate in the market, taking as given the costs of producing the information.

In this article, we focus our analysis in the networks of collaboration in two different market competition frameworks. We first study collaborations among banks operating in independent markets. Subsequently, we study collaborations in a homogeneous-product oligopoly environment with quantity-setting banks. In particular, in the third stage, we assume that the n banks compete a la Cournot.

2.1 Networks Notation and Specification of the Model

Networks

Let $N = \{1, 2, ..., n\}, n \geq 2$ be the set of banks. The structure of alliances between the banks can be described as a non directed graph, in which nodes represent the banks and edges the collaboration links or alliances. A typical graph of alliances g is thus a pair (N, L) where N is a set of banks and L is a subset of all pairs of banks. Let denote by G the set of all non directed graphs with N banks. Let $g_{ij} \in \{0, 1\}$ be a binary variable that represents the pair-wise relationship between any pair of banks i,$j \in N$. The variable $g_{ij} = 1$ if there exists a link between two banks i and j and 0 otherwise. A network g is then a collection of links, i.e., $g = \{g_{ij}\}_{i,j\in N}$. Let $g - g_{ij}$ denote the network obtained by deleting an existing link between banks i and j from network g, while $g + g_{ij}$ is the network obtained by adding a new link between banks i and j in network g. Let $N_i(g)$ be the set of banks with which bank i forms a link in the graph g and $\eta_i(g)$ represents the cardinality of set $N_i(g)$ or bank $i's$ degree.

Let's define some basic network architectures that will be use in our analysis. A network is said to be *regular* if every bank has the same number of links, i.e., $\eta_i(g) = \eta$, $\forall i \in N$. The *complete* network, g^c, is a regular network such that $\eta_i(g) = \eta - 1$, $\forall i \in N$ while the *empty* network, g^e, is a regular network in which $\eta_i(g) = 0$. Other network architectures are the *star* network, g^s, in which there is one bank which is linked to the others banks. Formally, there is a bank i such that $g_{i,j} = 1$ for all $j \neq i$ and $g_{i,j} = 0$ for every pair of banks $j, k \neq i$. The *unconnected* network, g^u, is the one in which one bank is isolated and the other banks have at least one link.

Cost Structure and Collaboration Alliances

We assume a market with n banks that are ex-ante symmetric, with zero fixed cost and identical marginal costs $\overline{c}$. Before competition takes place, banks can individually invest in some marginal-cost-reducing technology with the goal of gaining more market power on the competition stage. Moreover, banks can engage in non-exclusive collaboration agreements to share and reduce the costs of R&D efforts. Any agreement to jointly invest in some cost-reducing technology or activity will be interpreted in our framework as a collaboration link.

A particular network architecture will arise after all the banks in the market have decided how to undertake their cost-reducing investment projects, either in isolation or in collaboration with others banks. Then, given some network g, each bank chooses unilaterally an R&D effort level, $e_i \in E = [0, \overline{c}]$, with the goal of lowering its own marginal cost. Individual efforts also have positive spillover externalities on the costs of other banks. Let $\psi \in [0, 1)$ be a parameter that reflects the level of spillovers among banks with no collaboration links. If two banks have a collaboration link, then this spillover is perfect, and if they do not have a collaboration link, then this spillover is imperfect.Thus, the marginal cost of production of bank i can be expressed as following,

$$c_i(e/g) = \overline{c} - \left(e_i + \sum_{j \in N_i(g)} e_j + \psi \sum_{m \notin Ni \cup \{i\}} e_m \right)$$

For simplicity, we assume that the effort of any bank exclusively and fully spills over its partners. Furthermore, there are no spillovers from outside the industry. In others words, $\psi = 0$. Thus, the effective marginal costs of production of a bank i, given network g and a profile of efforts levels $\{e_i(g)\}_{i \in N}$ are

$$c_i(e/g) = \overline{c} - \left(e_i + \sum_{j \in N_i(g)} e_j \right) \tag{1}$$

In this specification, marginal cost of i decreases linearly in the number of banks belonging to the same coalition as i. Observe that the total cost reduction for some bank i comes from its own research effort e_i, and the research effort of others banks. Moreover, we assume that R&D effort is costly. Formally, we use the following specification $Z(e_i) = \theta\, e_i^2$ where $\theta > 0$ and sufficiently large to ensure bank decision problems have interior solutions. In other words, it ensures profit function is concave in own effort. Under this specification, the cost of R&D effort is a non-decreasing function and exhibits decreasing returns to scale.

Payoffs

A network of collaboration g leads to a vector of R&D efforts $\{e_j(g)\}_{i \in N}$, which in turn defines the banks' production costs $\{c_i(g)\}_{i \in N}$. Given these marginal costs, banks operate in the market by choosing quantities $\{q_i(g)\}_{i \in N}$. The inverse demand is assumed to be linear and given by $P = a - b\, Q$, with $a > \overline{c}$.

In the independent market case, $Q = q_i$, and the profits of bank i in collaboration network g are

$$\Pi_i(g) = [a - b\, q_i(g) - c_i(g)]\, q_i - \theta\, e_i^2(g) \qquad \forall i = 1, \ldots, n \tag{2}$$

In the homogeneous-good market with quantity-setting banks, $Q = \sum_{i=1}^{n} q_i$. Thus, the profits of bank i in collaboration network g are given by,

$$\Pi_i(g) = \left[a - b\, q_i(g) - b \sum_{j \neq i} q_j(g) - c_i(g)\right] q_i(g) - \theta\, e_i^2(g) \qquad \forall i = 1, \ldots, n \tag{3}$$

Networks Stability

A network g is said to be stable if any bank that is linked to another in the network has an incentive to maintain the link and any two banks that are not linked have no incentive to form a link with each other. This definition follows the notion of stability presented in **?**. Formally, a network g is *stable* if and only if for all $i, j \in N$,

(i) if $g_{ij} = 1$, then $\pi_i(g) \geq \pi_i(g - g_{ij})$ and $\pi_j(g) \geq \pi_j(g - g_{ij})$.

(ii) if $g_{ij} = 0$ and $\pi_i(g + g_{ij}) > \pi_i(g)$, then $\pi_j(g + g_{ij}) < \pi_j(g)$.

This definition of stability, which is taken from **?**), is quite weak and should be seen as a necessary condition for strategic stability for any given network.

Efficiency

For any network g, social welfare is defined as the sum of consumer surplus and producers' profits. If we denote aggregate welfare as $W(g)$ for any network g, we say that a network g is efficient if and only if $W(g) > W(g')$ for all g'. This concept of efficiency is in the spirit of a second best, since efforts and quantities are chosen within a noncooperatively framework. When banks operate in *independent markets*, social welfare is describe by the following expression,

$$W(g) = \sum_{i=1}^{n} \left(\frac{q_i^2(g)}{2} + \pi(g) \right) \tag{4}$$

Let $Q(g) = \sum_{i=1}^{n} q_i(g)$ be the aggregate output in network g for the homogeneous-product oligopoly. In this case, it is easily seen that

$$W(g) = \frac{Q(g)^2}{2} + \sum_{i=1}^{n} \pi(g) \tag{5}$$

Symmetric Networks

A network is said to be symmetric if every bank has the same number of collaboration links. In a symmetric network $\eta_i(g) = \eta_j(g) = k$ for any two banks i and j. The number k will be referred to as the degree of network g or, equivalently, as the level of collaborative activity. We will denote a symmetric network of degree k by g^k, $k = 0, 1, ..., n-1$. It is worth emphasizing that symmetric networks allow for nonexclusive relationships. For example, a symmetric network of degree two involves a bank having links with banks that are not linked to each other. Note that if the number of banks is even, then there is always a set of links l such that the resulting network is symmetric of degree k, where $k = 0, 1, ..., n-1$.

2.2 Independent Markets Case

We first present the model for a general firm and in the next section we applied the model for the banking industry. Collaborations between firms operating in independent markets are commonly observed. In such an environment, individual R&D effort has no implications for the level of market competitiveness of potential collaborators. This setting therefore allows us to isolate the pure effects of collaboration. We find that collaboration between firms increases the level of effort by individual firms. Moreover, every pair of firms has an incentive to form links, and the complete network is the unique stable and efficient network.

Market Outcome. Given a network g, and the R&D efforts levels $\{e_i(g)\}_{i\in N}$, firms choose quantities to maximize their monopoly profits given by expression (2) above. Standard derivations show that equilibrium quantities are $q_i(g) = [a - c_i(g)]/2b$ for all i, which yield the following profit function after we had plugged them back into (2).

$$\Pi_i(g) = \frac{[a - c_i(g)]^2}{4b} - \theta\, e_i^2(g)$$

$\forall i = 1, \ldots, n(6)$

R&D Efforts. In the second stage of the game, firms choose their R&D efforts to maximize the reduced-form profits (6). The costs $c_i(g)$ depend on the effort levels undertaken by the firms, which in turn are a function of the existing network. Therefore, using (1) and the fact we consider only symmetric networks of degree k, we obtain

$$\Pi_i(g^k) = \frac{\left[a - \bar{c} + e_i + \sum_{l \in N_i(g)} e_l\right]^2}{4b} - \theta\, e_i^2(g)$$

$\forall i = 1, \ldots, n(7)$

We observe in the expression above that the profits of bank i are a non-decreasing and convex function of the efforts of banks that have some collaborative agreement with bank i. In other words, the efforts of collaborating banks are strategic complements. From the first order condition, $(a - \bar{c} + e_i + \sum_{l \in N_i(g)} e_l) - 4b\,\theta\, e_i^2 = 0$ and by invoking symmetry, we obtain the following simple expression for the equilibrium R&D efforts,

$$e_i^*(g^k) = \frac{(a - \bar{c})}{[4b\theta - (k+1)]} \quad \forall i = 1, \ldots, n \tag{8}$$

We can also analyse the nature of the equilibrium marginal cost reduction by substituting (8) into the cost structure $c_i = \bar{c} - (k+1)e_i^*$ given by (1) and using the fact we consider only symmetric networks of degree k, we obtain

$$c_i^*(g^k) = \bar{c} - \frac{(k+1)\,(a - \bar{c})}{[4b\theta - (k+1)]} \quad \forall i = 1, \ldots, n \tag{9}$$

Finally, by substituting the equilibrium level of efforts obtained in (8) into (7) we can examine the nature of equilibrium profits given by

$$\Pi_i^*(g^k) = \frac{(a - \bar{c})^2\,\theta\,(4b\theta - 1)}{[4b\theta - (k+1)]^2} \quad \forall i = 1, \ldots, n \tag{10}$$

Proposition 1 *Assume firms operate in independent markets. Then individual R&D efforts and profits are increasing with respect to the level of collaborative activity while marginal costs are decreasing.*

Proof. See Appendix.

2.3 Homogeneous-product oligopoly

In the previous section, we tried to provide an explanation why collaborations between firms operating in independent markets were commonly observed. In such an environment, individual R&D effort had no implications for the level of market competitiveness of potential collaborators, isolating the pure effects of collaboration.

In this section, we follow the method of **?**,and study collaborations between firms operating in the same market. In this new setting, a firm's R&D effort lowers the costs of its collaborators, which in this setting makes them more competitive. This reduces the marginal returns to investing in R&D as additional links of collaborations are formed. The analysis illustrates how this competition effect influences the private and social incentives to collaborate. Their first observation concerns the effects of collaboration on the R&D effort of individual firms.

Market outcome. In the market competition stage, we note that given a cost configuration of firms, $\{c_i(g)\}_{i \in N}$, the equilibrium quantity of bank i in a homogeneous-product oligopoly is obtained by solving firm $i's$ optimization problem given by (3).

$$q_i(g) = \frac{1}{(n+1)\,b}\left[a - n\,c_i(g) + \sum_{j \neq i} c_j\right] \quad \forall i = 1, \ldots, n \tag{11}$$

Substituting for the equilibrium value of $q_i(g)$ in the profit function given by (3), we are left that the profits of the Cournot competitors are given by the following expression:

$$\Pi_i(e/g^k) = \frac{\left[a - n\,c_i(e/g) + \sum_{j \neq i} c_j(e/g)\right]^2}{b\,(n+1)^2} - \theta\, e_i^2(g) \quad \forall i = 1, \ldots, n \tag{12}$$

The derivations in the appendix allow us to express the payoffs in terms of research efforts directly. In particular, the pay-offs to a bank i, located in a regular network g of degree k, faced with a research profile e, are

$$\Pi_i(g^k) = \frac{\left[a - \overline{c} + e_i(n-k) + e_j(n-k)k - e_l(k+1)(n-k-1)\right]^2}{b\,(n+1)^2} - \theta\, e_i^2 \tag{13}$$

Note that we use the symmetry for the connected and non-connected firms with respect to firm i, respectively. From the first order condition and invoking symmetry, i.e., $e_i = e_j = e_l = e(g^k)$ and solving for $e(g^k)$ we obtain the equilibrium effort level:

$$e^*(g^k) = \frac{(a - \overline{c})\,(n-k)}{\left[b\,(n+1)^2 - (k+1)\,(n-k)\right]} \tag{14}$$

Our first observation is that this equilibrium level of R&D effort is declining (at least locally) in the level of collaborative activity k. We establish this by showing that

$$\frac{\partial e^*(g^k)}{\partial k} = \frac{(a - \overline{c})\left[(n-k)^2 - b\,\theta\,(n+1)^2\right]}{\left[b\,(n+1)^2 - (k+1)\,(n-k)\right]^2} < 0 \tag{15}$$

To examine the effect of the number of connections on the nature of cost reduction we substitute (14) into the cost structure (1) and we are left that equilibrium costs are expressed as following:

$$c^*(g^k) = \frac{\overline{c}\,b\,\theta\,(n+1)^2 - a\,(k+1)\,(n-k)}{\left[b\,(n+1)^2 - (k+1)\,(n-k)\right]} \tag{16}$$

We observe that cost are decreasing at low level of connections and then increasing at higher level of collaborative links. Thus, minimum costs are attained at an intermediate level of collaboration. This result is obtained formally by calculating the derivative of equilibrium costs with respect to the degree.

$$\frac{\partial c^*(g^k)}{\partial k} = \frac{(2k+1-n)\,(a - \overline{c})\,b\,\theta\,(n+1)^2}{\left[b\,(n+1)^2 - (k+1)\,(n-k)\right]^2} \tag{17}$$

It is easy to see that an increase in the level of collaborations reduces the cost of the banks if and only if $k < (n-1)/2$. Thus, cost reduction exhibits a nonmonotonic relationship with respect to the density of the network.

Finally, the profits attained by a bank in a symmetric network of degree k can be obtained by substituting the equilibrium level of effort into (13):

$$\Pi_i(g^k) = \frac{\theta\,(a-\bar{c})^2\left[b\,\theta\,(n+1)^2-(n-k)^2\right]}{\left[b\,(n+1)^2-(k+1)\,(n-k)\right]^2} \tag{18}$$

Profits are initially increasing and then eventually falling with respect to the degree of the number of links (degree). We establish this by taking the derivative of equilibrium profits with respect to degree.

$$\frac{\partial \Pi_i(g^k)}{\partial k} = \frac{\theta\,(a-\bar{c})^2\,(n-k)\left[\left(b\,\theta\,(n+1)^2-(n-k)^2\right)+b\,\theta\,(n+1)^2\,(n-2k-1)\right]}{\left[b\,(n+1)^2-(k+1)\,(n-k)\right]^3} \tag{19}$$

Note that the denominator is positive. In the numerator all the expressions are positive as long as $k < (n-1)/2$. This implies that equilibrium profits are increasing in degree when the number is connections is small.

The following result, due to **?** summarizes the analysis on symmetric network of collaboration in oligopoly markets.

Proposition 2 *Consider a homogeneous good market where firms compete in quantities and suppose that banks are located in a regular network of collaboration. The following network effects arise. (i) Research effort of a firm is decreasing in the level of collaborative activity. (ii) Relationship between cost reduction and the level of collaborative activity is non-monotonic. Cost are initially decreasing and then increasing with respect to degree. (iii) Profits are initially increasing but eventually falling with respect to degree.*

Proof. See Appendix.

This section has shown that in homogeneous good market where firms compete *a lá Cournot* and where banks are located in a regular network of collaboration, profits are maximized at an intermediate level of collaborative activity. In the next section, we present an application of these models of networks collaboration using a revised version of the Monti-Klein model of banking or the industrial organization model of banking.

3 Application: The Monti-Klein Model of Banking in a Network Approach

Information is one of the basic inputs needed by a bank to survival in the marketplace. Unfortunately, in general the data needed to screen credit applications and to monitor borrowers are not freely available to banks. Collecting and processing information efficiently in screening credit applicants and in monitoring their performance is costly. At the screening stage, lenders need information about borrowers characteristics, including the riskiness of their investment projects. To the extent that a bank does not have such information, it faces adverse selection problems in its lending activity. Adverse selection arises when some information about the borrowers characteristics remain hidden to the lender (hidden information), and can lead to an inefficient allocation of credit, for instance to its rationing or to an increase in the cost of managing certain volume of loans.

One mechanism a bank can follow to reduce this information asymmetry problem (and the marginal cost of producing a loan) is to invest in some sort of cost-reducing technology. It can acquire the information about customers that it does not possess by spending resources to collect information about them. At the screening stage, it can visit the credit applicants plants, talk to their managers, and study their business plans.

However, it is often cheaper and more effective to acquire information by exchanging it with other lenders. Therefore, we consider an oligopoly market with (ex ante) identical banks. Prior to market interaction, each bank has an opportunity to form pair-wise collaborative links with other banks. The purpose of these ties is to share credit information with goal of reducing the information asymmetry cost. The collection of pair-wise links between the banks defines a network of collaboration.

Given a collaboration network, banks unilaterally choose a (costly) level of effort in research and development, R&D , aimed at reducing the intermediation costs. The level of effort of different banks and the network of collaboration define the effective costs of the different banks in the market. Given these costs, banks operate in the market by setting quantities. We consider two types of market interaction: in the first case, banks operate in independent markets, while in the second case, they compete *a lá Cournot* in a homogeneous-service market.

We model banking activity as the production of deposit and loan services. Banking technology is represented by a cost function $C(D, L)$ interpreted as the cost of managing a volume D of deposits and a volume L of loans.

3.1 Independent Markets Case

An imperfect competition model is probably more appropriate to analyse the banking industry since the assumption of perfect competition may not seem really appropriate for the this sector, where there are important barriers to entry. This discussion first studies the Monti-Klein model, which in its simplest version is poles apart from the perfectly competitive model because it considers a monopolistic bank.

There are n different banks (or regions), indexed by $i = 1, ..., n$ with the same cost function that satisfies the usual assumptions of convexity (which implies decreasing returns to scale) and regularity (C is twice differentiable). The inverse demand function for loans is given by $r_L(L)$, with derivative $r'_L(L) < 0$, and the inverse supply function of deposits is r_D, with derivative $r'_D(D) > 0$. We also assume that borrowers might apply for loans in one or more banks (regions) at the same time.

Assume that the bank i takes the interbank rate r as given, either because it is fixed by the Central Bank or because it is determined by the equilibrium rate on international capital markets. The coefficient α of compulsory reserves may be used as a policy instrument through which the Central Bank tries to influence the quantity of money in circulation in the economy.

In its more general version, the bank's decision problem is to maximize its profits given by the following expression:

$$\Pi_i(L_i, D_i) = [r_L(L_i) - r]\, L_i + [r(1-\alpha) - r_D(D_i)]\, D_i - C_i(L_i, D_i) \tag{20}$$

The bank's profit is basically the sum of the intermediation margins on loans and on deposits minus management costs. We assume that $\Pi(L, D)$ is strictly concave in order for the maximum of π_i to be characterized by the following first-order conditions,

$$\frac{\partial \Pi_i}{\partial L_i} = r'_L(L_i)L_i + r_L - r - \frac{\partial C(L_i, D_i)}{\partial L_i} = 0 \tag{21}$$

$$\frac{\partial \Pi_i}{\partial D_i} = -r'_D(D_i)D_i + r(1-\alpha) - r_D - \frac{\partial C(L_i, D_i)}{\partial D_i} = 0 \tag{22}$$

For simplicity in the exposition, we assume that management costs are additive for bank i. In particular, the cost is linear in L and D, i.e., $C(D, L) = C_i^L L + C_i^D D$. The separability of the cost function leads to the following important result:

Lemma 1 *If management costs are additive, the bank's decision problem is separable. In others words, the optimal volume of deposits (and the corresponding deposit rate) is independent of the characteristics of the loan market, and the optimal volume of loans (and and the corresponding loan rate) is independent of the characteristics of the deposit market.*

Proof. The lemma can be easily proved by looking at the first order conditions (21) and (22). Since management costs are additive, the bank's decision problem is separable. Formally, $\partial C(L_i, D_i)/\partial L_i = \partial C(L_i)/\partial L_i$ if $\partial C(L_i, D_i)/\partial L_i \partial D_i = 0$. QED.

Further, the version of the Monti-Klein model considered here refers to a monopolistic commercial bank that operates in region i confronted with a linear downward-sloping inverse demand for loans, $r_L(L) = a_L - b_L L$ and a linear upward-sloping supply of deposits, $r_D(D) = a_D + b_D D$. The discussion here is in line with the more traditional view of a banks buying funds from depositors and selling them to borrowers. It therefore speaks of a demand for loans by borrowers and a supply of deposits by households.Indeed, granting a loan is equivalent to buying a security issued by the borrower. Similarly, collecting deposits is like issuing securities. The bank's decision variables are L (the amount of loans) and D (the amount of deposits), since its level of equity is assumed to be given.

Now, under these specification, the bank's profit equation (20) can be re-expressed as

$$\Pi_i(L, D) = \left[a_L - b_L L_i - r - C_i^L\right] L_i + \left[r(1-\alpha) - a_D - b_D D_i - C_i^D\right] D_i \qquad (23)$$

Next, we assume that collaborations between banks operating in independent markets are possible. Recall, that the purpose of these ties is to share credit information with goal of reducing the information asymmetry cost that arises when some information about the borrowers characteristics remain hidden to the lender, leading to an inefficient allocation of credit. Then, the research effort by an individual bank is directly related with the acquisition of information about borrowers that it does not possess. However, collecting information (research effort) is costly for the bank. Formally, we use the following specification $Z(e_i) = \theta\, e_i^2$ where $\theta > 0$ and sufficiently large to ensure bank decision problems have interior solutions. Then, the profit function reflecting these specifications is given by

$$\Pi_i(L, D) = \left[a_L - b_L L - r - C_i^L\right] L_i + \left[r(1-\alpha) - a_D - b_D D - C_i^D\right] D_i - \theta\, e_i^2 \qquad (24)$$

In this setting, research effort has no implications for the level of market competitiveness of potential collaborators. Therefore, we isolate the pure effects of collaboration. We find that collaboration between banks increases the level of effort by individual banks. Moreover, every pair of banks has an incentive to form links, and the complete network is the unique stable and efficient network.

Recall that a particular network architecture will arise after all the banks in the market have decided how to undertake their cost-reducing investment projects, either in isolation or in collaboration with others banks. Now, given some network g, every bank chooses unilaterally an R&D effort level, e_i, with the goal of lowering its own marginal cost of managing the loans. Formally,

$$C_i^L(e/g) = \gamma_L - \left(e_i + \sum_{j \in N_i(g)} e_j \right) \tag{25}$$

In this specification, marginal cost of i decreases linearly in the number of banks belonging to the same coalition as i. Observe that the total cost reduction for some bank i comes from its own research effort e_i, and the research effort of others banks. Finally, we assume that the marginal cost of managing the deposits are small and constant, i.e. $C_i^D = \overline{C_D}$. In others words, the research efforts are focussed to reduce the marginal cost of managing the loans.

Market outcome. Given a network g, and the R&D efforts levels $\{e_i(g)\}_{i \in N}$, banks choose quantities to maximize their monopoly profits given by expression (24). Standard derivations show that the equilibrium volume of loans and deposits are given by the following expressions respectively,

$$L_i^*(g) = \frac{[a_L - r - C_i^L(g)]}{2b_L} \tag{26}$$

$$D_i^*(g) = \frac{[r(1-\alpha) - \overline{C_D} - a_D]}{2b_D} \tag{27}$$

which yield the following profit function after we had plugged them back into (24).

$$\Pi_i(g) = \frac{\left[a_L - r - C_i^L(g)\right]^2}{4b_L} + \frac{[r(1-\alpha) - \overline{C^D} - a_D]^2}{4b_D} - \theta\, e_i^2(g)$$

$\forall i = 1, \ldots, n(28)$

For comparison purposes with the theoretical model presented in section 1, we rewrite the previous equation as

$$\Pi_i(g) = \frac{\left[a_L - c_i^L(g)\right]^2}{4b_L} - \theta\, e_i^2(g) + \Delta_D$$

$\forall i = 1, \ldots, n$(29)

where $\Delta_D = [r(1-\alpha) - \overline{C_i^D} - a_D]^2/4b_D$ can be ignored from the analysis that follows. Recall that when management costs are separable the problem of choosing the optimal volume of loans can be found independently of the characteristics of the market for deposits. We have also defined $c_i^L(g) = r + C_i^L(g) = r + \gamma_L - (e_i + \sum_{j\in N_i(g)} e_j)$. Now, if we define $\overline{c_L} = r + \gamma_L$ we are left with the same marginal cost structure presented in the theoretical model in section 1, that is, $c_i^L(g) = \overline{c_L} - (e_i + \sum_{j\in N_i(g)} e_j)$.

In this way, we can restate all of the results that we found in the theoretical model presented in section 1 and some additional results concerning monetary policy.

R&D efforts. In the second stage of the game, banks choose their R&D efforts to maximize the reduced-form profits (29). The costs $c_i(g)$ depend on the effort levels undertaken by the banks, which in turn are a function of the existing network. Therefore, using (25) and the fact we consider only symmetric networks of degree k, we obtain

$$\Pi_i(g^k) = \frac{\left[a_L - \overline{c_L} + e_i + \sum_{l\in N_i(g)} e_l\right]^2}{4b_L} - \theta\, e_i^2(g) + \Delta_D$$

$\forall i = 1, \ldots, n$(30)

We observe in the expression above that the profits of bank i are a non-decreasing and convex function of the efforts of banks that have some collaborative agreement with bank i. In other words, the efforts of collaborating banks are strategic complements. From the first order condition, and by invoking symmetry, we obtain

$$e_i^*(g^k) = \frac{(a_L - \overline{c_L})}{[4b_L\theta - (k+1)]} \quad \forall i = 1, \ldots, n \tag{31}$$

We can also analyse the nature of the equilibrium marginal cost reduction by substituting (31) into the cost structure $c_i^L = \overline{c_L} - (k+1)e_i^*$ and obtain

$$c_i^*(g^k) = \overline{c_L} - \frac{(a_L - \overline{c_L})(k+1)}{[4b_L\theta - (k+1)]} \quad \forall i = 1, \ldots, n \tag{32}$$

Finally, by substituting the equilibrium level of efforts obtained in (31) into (30) we can examine the nature of equilibrium profits

$$\Pi_i^*(g^k) = \frac{(a_L - \overline{c_L})^2 \theta (4b_L\theta - 1)}{[4b_L\theta - (k+1)]^2} + \Delta_D \quad \forall i = 1, \ldots, n \tag{33}$$

Proposition 3 *Assume banks operate in independent markets (or regions). Then individual research efforts and profits are increasing with respect to the level of collaborative activity while marginal costs of managing loans are decreasing.*

Proof. See Proposition 2.

Our framework can also be used to study the effects of an increase in the level of credit sharing information among banks on the net position of the bank in the interbank market. Recall that M_i is the net position of the bank i on the interbank market, and is given by,

$$M_i^* = (1-\alpha)D_i^* - L_i^* \quad \forall i = 1, \ldots, n \tag{34}$$

Proposition 4 *Assume banks operate in independent markets (or regions). Then the volume of the net position of the bank i in the interbank markets falls when there is an increase in the level of collaborative activity among banks.*

Proof. Let's begin with the optimal volume of loans given by $L_i^* = [a_L - C_i^L]^2/2b_L$. It is easy to see that $\partial L_i^*/\partial k = -(1/2b_L)\partial C_i^L/\partial k$. Now, from Proposition 3, we know that the sign of the derivative $\partial C_i^L/\partial k < 0$, which implies $\partial L_i^*/\partial k > 0$. Therefore, $\partial M_i^*/\partial k < 0$. QED.

The intuition behind this result can be explained in the following terms. A commercial bank i can reduced the marginal cost of managing the loans by increasing the number of alliances or links with other banks. In particular, a bank now can increase the volume of loans funded with its on deposits. Thus, overall the increment in the sharing of credit information gives each bank more independence in the sense that it relies less on the interbank market to fund their daily operations.

Monetary Policy and Banking Collaborative Networks

In this section we consider the effects of monetary policy on the incentives of banks to share credit information (to form collaborative links) in the independent market case. Modern monetary policy is more accurately described as interventions on the rate r at which the Central Bank refinances commercial banks (assumed equal to the interbank rate). Another policy instrument through which the Monetary Authority tries to influence the level of credit in the economy is the coefficient of compulsory reserves α.

In our framework it is easy to see how an anti-cyclical monetary policy affect the incentive of commercial banks to share credit information. For example, the Central Bank may increase the coefficient of compulsory reserves α in good states, and decreases it in bad states.

Proposition 5 *Assume banks operate in independent markets (or regions). If the Central Bank increases the coefficient of compulsory reserves α, with the goal of contracting the level of credit in the economy, then commercial banks will react by increasing the number of collaborative activity among them.*

Proof. Start with the equilibrium profits expression given by (33). Now, by the implicit function theorem we know that

$$\frac{\partial k}{\partial \alpha} = -\frac{\partial \Pi_i^*/\partial \alpha}{\partial \Pi_i^*/\partial k} \tag{35}$$

We have already shown in Proposition 3 that $\partial \Pi_i^*/\partial k$ is positive. Now it is relatively easy to see from the equilibrium profit function that $\partial \Pi_i^*/\partial \alpha$ is negative. Therefore, $\partial k/\partial \alpha > 0$. QED.

Oligopolistic Banking and Sharing Credit Information Alliances

We extend the analysis to the case of n banks that interact within an oligopolistic banking framework. Basically, we reinterpret the Monti-Klein model as a model of imperfect *Cournot* competition between a finite number n of banks. Collaborations at the pre-competition stage between banks operating in the same market are aimed to reduced the high level of information asymmetry inherent in credit markets. Like in the previous case, a bank's R&D effort lowers the marginal cost of managing loans of its collaborators, which in this setting makes them more competitive. This reduces the marginal returns to investing in R&D as additional links are formed. This analysis illustrates how this competition effect influences the private and social incentives to collaborate. Again, we assume that the research effort by an individual bank is directly related with the acquisition of information about borrowers that it does not possess. Then, the profit function reflecting these specifications is given by

$$\Pi_i(L_i, D_i) = \left[a_L - b_L L_i - b_L \sum_{j \neq i} L_j - c_i^L\right] L_i + \left[c_i^D - a_D - b_D D_i - b_D \sum_{j \neq i} D_j\right] D_i - \theta\, e_i^2 \tag{36}$$

where $c_i^L = r + C_i^L$ and $c_i^D = r(1-\alpha) - C_i^D$.

Market outcome. In the market competition stage, we note that given a cost configuration of banks, $\left\{C_i^L(g)\right\}_{i \in N}$, the optimal volume of loans for bank i in a homogeneous-product oligopoly is given by

$$L_i^*(g) = \frac{1}{(n+1)\, b_L}\left[a_L - n\, c_i^L(g) + \sum_{j \neq i} c_j^L(g)\right] \quad \forall i = 1, \ldots, n \tag{37}$$

$$D_i^*(g) = \frac{1}{(n+1)\,b_D}\left[n\,c_i^D(g) - \sum_{j\neq i} c_j^D(g) - a_D\right] \quad \forall i = 1,\ldots,n \tag{38}$$

Substituting for the equilibrium value of $L_i(g)$ and $D_D(g)$ in the profit function (3), we are left that the profits of the Cournot competitors are given by the following expression:

$$\Pi_i = \frac{\left[a_L - n\,c_i^L + \sum_{j\neq i} c_j^L\right]^2}{b_L\,(n+1)^2} + \frac{\left[n\,c_i^D - \sum_{j\neq i} c_j^D - a_D\right]^2}{b_D\,(n+1)^2} - \theta\,e_i^2(g) \tag{39}$$

Let's define $\Delta_D = \left[n\,c_i^D - \sum_{j\neq i} c_j^D - a_D\right]^2 / b_D\,(n+1)^2$. Further, since individual research efforts do not affect the marginal cost of deposits, we can assume they are constant, i.e. $c_i^D = c_j^D = \overline{C^D}$ for all $j \neq i$, which left $\Delta_D = \left[\overline{C^D} - a_D\right]^2 / b_D\,(n+1)^2$. Then, we can rewrite the previous profit function as,

$$\Pi_i = \frac{\left[a_L - n\,c_i^L + \sum_{j\neq i} c_j^L\right]^2}{b_L\,(n+1)^2} - \theta\,e_i^2(g) + \Delta_D \tag{40}$$

Similar derivations like in section 1, allow us to express the payoffs in terms of research efforts directly. In particular, the payoffs to a bank i, located in a regular network g of degree k, faced with a research profile e, are

$$\Pi_i(g^k) = \frac{\left[a_L - \overline{c_L} + e_i(n-k) + e_j(n-k)k - e_l(k+1)(n-k-1)\right]^2}{b_L\,(n+1)^2} - \theta\,e_i^2 + \Delta_D \tag{41}$$

Note that we use the symmetry for the connected and non-connected banks with respect to bank i, respectively. From the first order condition and invoking symmetry, i.e., $e_i = e_j = e_l = e(g^k)$ and solving for $e(g^k)$ we obtain the equilibrium effort level:

$$e^*(g^k) = \frac{(a - \overline{c_L})\,(n-k)}{\left[b_L\,(n+1)^2 - (k+1)\,(n-k)\right]} \tag{42}$$

Our first observation is that this equilibrium level of R&D effort is declining (at least locally) in the level of collaborative activity k. We establish this by showing that

$$\frac{\partial e^*(g^k)}{\partial k} = \frac{(a_L - \bar{c})\left[(n-k)^2 - b_L\,\theta\,(n+1)^2\right]}{\left[b_L\,(n+1)^2 - (k+1)\,(n-k)\right]^2} \tag{43}$$

To examine the effect of the number of connections on the nature of cost reduction we substitute (42) into the cost structure (1) and we are left that equilibrium costs are expressed as following:

$$c_L^*(g^k) = \frac{\overline{c_L}\,b_L\,\theta\,(n+1)^2 - a_L\,(k+1)\,(n-k)}{\left[b_L\,(n+1)^2 - (k+1)\,(n-k)\right]} \tag{44}$$

We observe that cost are decreasing at low level of connections and then increasing at higher level of collaborative links. Thus, minimum costs are attained at an intermediate level of collaboration. This result is obtained formally by calculating the derivative of equilibrium costs with respect to the degree:

$$\frac{\partial c_L^*(g^k)}{\partial k} = \frac{(2k+1-n)\,(a_L - \overline{c_L})\,b_L\,\theta\,(n+1)^2}{\left[b_L\,(n+1)^2 - (k+1)\,(n-k)\right]^2} \tag{45}$$

It is easy to see that an increase in the level of collaborations reduces the cost of the banks if and only if $k < (n-1)/2$. Thus, cost reduction exhibits a non-monotonic relationship with respect to the density of the network.

Finally, the profits attained by a bank in a symmetric network of degree k can be obtained by substituting the equilibrium level of effort and costs into (39):

$$\Pi_i(g^k) = \frac{\theta\,(a_L - \overline{c_L})^2\left[b_L\,\theta\,(n+1)^2 - (n-k)^2\right]}{\left[b_L\,(n+1)^2 - (k+1)\,(n-k)\right]^2} + \Delta_D \tag{46}$$

Profits are initially increasing and then eventually falling with respect to the degree of the number of links (degree). We establish this by taking the derivative of equilibrium profits with respect to degree.

$$\frac{\partial \Pi_i(g^k)}{\partial k} = \frac{\theta\,(a_L - \overline{c_L})^2\,(n-k)\left[\left(b_L\,\theta\,(n+1)^2 - (n-k)^2\right) + b_L\,\theta\,(n+1)^2\,(n-2k-1)\right]}{\left[b_L\,(n+1)^2 - (k+1)\,(n-k)\right]^3} \tag{47}$$

Note that the denominator is positive. In the numerator all the expressions are positive as long as $k < (n-1)/2$. This implies that equilibrium profits are increasing in degree when the number is connections is small.

The following result summarizes the analysis on symmetric network of collaboration in banking oligopoly markets.

Proposition 6 *Consider a homogeneous loan market where banks compete in volume and suppose that banks are located in a regular network of collaboration. The following network effects arise. (i) Research effort of a bank is decreasing in the level of collaborative activity. (ii)relationship between cost reduction and the level of collaborative activity is non-monotonic. Cost are initially decreasing and then increasing with respect to degree. (iii) Profits are initially increasing but eventually falling with respect to degree.*

The main implication of this section is to show that in homogeneous loan market where banks compete a la Cournot and where banks are located in a regular network of collaboration, profits are maximized at an intermediate level of sharing credit information.

Monetary Policy and Banking Collaborative Networks

In this section we reconsider the effects of monetary policy on the incentives of banks to share credit information in the case of banks competing in a oligopolistic market. From the previous analysis, we concluded that bank's profits are maximized at an intermediate level of sharing credit information. In particular, we found that at low level of connections, that is for $k < (n-1)/2$, profits were increasing. On the other hand, when $k > (n-1)/2$ the bank would be too connected and profits will be decreasing.

The Monetary Authority can influence the degree of connection of the banking system by altering the coefficient of compulsory reserves α. If at some point in time, the Central Bank observes that the level of connections of the banking system is too low, it could increase α to provide more incentives to the banks to form additional links of collaborations. The following proposition summarizes this idea.

Proposition 7 *Assume banks operate in oligopolistic markets. If the Central Bank increases the coefficient of compulsory reserves α, then commercial banks will react by increasing(decreasing) the number of collaborative activity if and only if $k < (>)(n-1)/2$.*

Proof. Start with the equilibrium profits expression given by (33). Now, by the implicit function theorem we know that

$$\frac{\partial k}{\partial \alpha} = -\frac{\partial \Pi_i^* / \partial \alpha}{\partial \Pi_i^* / \partial k} \tag{48}$$

We have already shown in Proposition 6 that $\partial \Pi_i^* / \partial k$ is positive (negative) if and only if $k < (>)(n-1)/2$. Now, it is relatively easy to see from the equilibrium profit function that $\partial \Pi_i^* / \partial \alpha$ is negative. Therefore, $\partial k / \partial \alpha > (<)0$ if and only if $k < (>)(n-1)/2$. QED.

4 Conclusion

The literature has long stressed that banks face adverse selection or moral hazard problems in its lending activity leading to an inefficient allocation of credit. Screening credit applications may help to reduce the adverse selection problem and monitoring borrowers may help to ease the moral hazard problem, yet the production of information is costly.

A cheaper and more effective way to acquire information is by exchanging it with other lenders. However, the type, quality, quantity of data available, and information-sharing mechanism finds a limit in the set of legal provisions designed to protect individual privacy and vary greatly from country to country, giving rise to different types of "credit bureaus" or the more complex "syndicated loans".

In this article, we model the banking industry within a network framework that provide us with some useful insights on the optimal number of credit sharing information alliances individual banks should establish to maximize expected profits, taking into account the different market structure in which they interact.

We find that if banks operate in independent markets,then individual research effort is increasing in the level of collaborative activity. Cost reduction and social welfare are maximized under the complete network, which is also the unique strategically stable network. These results imply that it is optimal that each bank shares credit information with all the other banks. This is in line with the tendency of credit bureaus - that were set up originally by small coalitions of lenders as cooperative arrangements - to be totally integrated in a few big credit agencies.

In the other hand, we find that if banks are *Cournot* competitors, in a homogeneous loan market, where banks compete in volume and banks are located in a regular network of collaboration, the following network effects arise: (i) Research effort of a bank is decreasing in the level of collaborative activity. (ii)relationship between cost reduction and the level of collaborative activity is non-monotonic. Cost are initially decreasing and then increasing with respect to degree. (iii) Profits are initially increasing but eventually falling with respect to degree. These results imply that banks profits are maximized at an intermediate level of sharing credit information and provide an alternative explanation why we observe syndicated loans even in countries in which formal sharing information systems are well established.

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