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CONJECTURAL GUARANTEES LOOM LARGE: EVIDENCE FROM THE STOCK RETURNS OF FANNIE MAE AND FREDDIE MAC*

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Abstract

Fannie Mae and Freddie Mac are government-sponsored enterprises (GSEs) with publicly traded equity. Although these companies hold government-issued charters, their securities are not legally backed by the full faith and credit of the United States government. Yet, investors and rating agencies seem to believe that the U.S. Government would "bail out" Fannie or Freddie if they became distressed. We provide evidence of a conjectural guarantee in GSE stock returns. Stock that contains an option on returning the shares at a given price to the issuer—the government, in this case—show pronounced nonlinearity (convexity) in the sensitivity of its return to market return. Using non-parametric methods on daily stock returns, we find that the GSEs' returns are less responsive to market movements the more sharply the market declines. Our findings are consistent with a government guarantee in GSE stock against catastrophic losses but not against atrophic losses.

1. Introduction

Fannie Mae and Freddie Mac are two of the largest financial institutions in the world. Together, they held about $1.5 trillion of assets (mostly mortgages and mortgage-backed securities) on June 30, 2003.[1] In addition, they had guaranteed against default another $2 trillion of mortgages owned by others in the form of mortgage-backed securities. The amount of on-balance sheet assets and off-balance sheet guaranteed assets of Fannie and Freddie is, approximately, equal to the amount of publicly held debt of the United States Government.

Fannie and Freddie are government-sponsored enterprises (GSEs) with publicly traded equity. Investors and rating agencies generally believe, while government officials and the enterprises themselves deny, that the U.S. Government would "bail out" Fannie or Freddie if they became distressed. While investing in and guaranteeing mortgages against default have been very profitable business lines in recent years, the potential for loss from mortgage defaults or interest-rate shocks clearly is present and may be sizable. Each institution has (book) equity capital of only about three percent of on-balance sheet assets. Yet the senior unsecured debt securities of both Fannie Mae and Freddie Mac are rated AAA by all major rating agencies for all maturities over one day.[2] Even the subordinated debt securities of the two enterprises receive ratings in the range AA− to AA, which is as high as senior debt securities issued by the strongest commercial banks or their holding companies. Banking organizations, meanwhile, hold about three times as much capital while enjoying both implicit and explicit guarantees on a substantial portion of their liabilities in the form of deposit insurance.

How can Fannie Mae and Freddie Mac issue senior debt at yields only slightly above those of U.S. Treasury securities, even though these issues are not legally backed legally by the full faith and credit of the U.S. Government? The answer to this question is clearly related to their status as "government-sponsored" financial institutions. All the major rating agencies make this argument explicitly when justifying the AAA ratings they bestow on all Fannie and Freddie senior obligations.

Investors apparently derive a great deal of comfort from a "conjectural guarantee" of some sort—that is, the expectation that neither Fannie Mae nor Freddie Mac would be allowed by the federal government or its agencies (such as the Federal Reserve) to default on its senior obligations. Of course, the existence of a conjectural guarantee has implications for the pricing of all financial claims issued by these companies. This paper explores what such a conjectural guarantee might mean for the behavior of Fannie Mae's and Freddie Mac's equity securities. Specifically, we estimate for the two companies the sensitivity of the daily stock return to the daily return on a market index over the period 1991-2002. We find pronounced convexity in the relation between both Fannie Mae's and Freddie Mac's returns and market returns, a pattern of stock returns consistent with the existence of a put option embedded in the GSE stock.

Section 2 of the paper describes the institutional framework in which Fannie Mae and Freddie Mac operate. The third section introduces the view of GSE stock as an equity claim with an embedded put option. Section 4 offers a formal analysis of the behavior of common stock with an embedded put option and derives testable hypotheses. Section 5 describes our empirical approach. Section 6 discusses model selection and the analysis of variance. Section 7 offers graphical representations of our results, and Section 8 concludes.

2. The Government-Related Housing-Finance Enterprises

The Federal National Mortgage Association (FNMA, or Fannie Mae) and the Federal Home Loan Mortgage Corporation (FHLMC, or Freddie Mac) are housing-related government-sponsored enterprises.[3] This means that they hold federal government-issued charters and, by law, are required to promote homeownership through enhancing the availability of financing for low- and moderate-income house purchases. At the same time, these companies are stockholder-owned corporations, so management owes a fiduciary responsibility to the owners to maximize shareholder wealth. A federal regulator enforces both affordable-housing business-volume targets and safety-and-soundness standards of operation. Capital markets impose discipline on management to generate adequate returns on invested capital. What capital-markets participants believe the public-policy mandates of the GSEs imply for the federal government's propensity to rescue these enterprises from financial distress is the subject of this paper.[4]

The nature of Fannie Mae's and Freddie Mac's involvement in housing finance has changed over time. They receive certain privileges related to their federal charters, such as exemption from state and local taxation and from SEC securities-registration requirements. Since 1992, they have been supervised by the Office of Federal Housing Enterprise Oversight (OFHEO), a single-purpose regulator that is housed in the Department of Housing and Urban Development (HUD. Congress currently is discussing a reform of the regulatory framework that would shift responsibility to the Treasury Department.

Other government-related housing-finance enterprises are the Federal Home Loan Bank System (FHLBS) and the Government National Mortgage Association (GNMA, or Ginnie Mae). The FHLBS was created by Congress in 1932 for the purpose of providing liquidity to thrift institutions. The 12 FHLBanks are private, co-operative enterprises, owned by the member depository institutions they serve. The organizational structure of the FHLB System resembles the Federal Reserve System with its 12 Federal Reserve Banks, each owned by member banks in its district. As explained below, Ginnie Mae emerged from Fannie Mae, which had been chartered by the Reconstruction Finance Corporation in 1938 to purchase Federal Housing Authority (FHA)-insured home mortgages. The mortgage portfolio was financed by issuing debt in public capital markets.

The government-sponsored housing-finance enterprise system that had been created during the Great Depression was restructured in two steps in 1968 and 1970. First, Fannie Mae was split into two parts in 1968. Ginnie Mae was created as a new government agency within the Department of Housing and Urban Development (HUD) to purchase FHA- and Veterans Administration (VA)-insured mortgages. Ginnie Mae's debt and mortgage-backed securities are backed by the full faith and credit of the United States Government; that is, Ginnie Mae is the only true "agency" among the four government-related housing enterprises that are commonly (and mistakenly) referred to as "agencies." Fannie Mae, meanwhile, was spun off as a privately owned but government-sponsored enterprise to purchase non-FHA or non–VA insured home mortgages from commercial banks and other mortgage originators.

The general-obligation debt and mortgage-backed securities issued by (the new) Fannie Mae are not and never were backed by the full faith and credit of the U.S. Government. Instead, they are backed explicitly by the underlying mortgage collateral and Fannie Mae's capital and, possibly, implicitly by a conjectural guarantee by the U.S. Government. The existence of an unwritten bailout policy is not fanciful—Fannie Mae was insolvent on a mark-to-market basis during the early 1980s but the federal government took no action to close it, and financial markets registered very little concern that the enterprise would not survive. A few years later another GSE, the Farm Credit System, was bailed out explicitly by Congress with a multibillion-dollar recapitalization.

The second step in restructuring the government-related housing-finance enterprise system consisted of the Federal Home Loan Bank System spinning off a new government-sponsored enterprise to purchase mortgages originated by thrift institutions—the new Freddie Mac. The same thrifts that co-operatively owned the FHLBanks became owners of Freddie Mac. In 1989, equity in Freddie Mac was sold to the general public. The new GSE's specific mandate was to create and support a secondary market for mortgage-backed securities (as opposed to Fannie Mae's mandate merely to purchase and hold mortgages). Like Fannie Mae, Freddie Mac issues general-obligation debt and mortgage-backed securities that are not and never were backed by the full faith and credit of the U.S. Government. Thus, while Ginnie Mae, the FHLBanks, Fannie Mae, and Freddie Mac all focus on housing finance, only the latter two have publicly traded equity. Only Ginnie Mae has the explicit backing of the U.S. Government, while capital markets appear to treat the other three GSEs as if they were backed by the federal government in one way or another.

3. Exploring the Characteristics of Daily Returns on GSE Stocks

In this section, we build intuition for the characteristics of GSE stock returns. To this end, we make specific assumptions about the type of option we hypothesize may be embedded in each GSE's stock. In the following section, we provide a more general theoretical framework from which we derive two hypotheses concerning important characteristics of GSE stock returns.

Conceptually, the put option embedded in Fannie Mae and Freddie Mac stock may be thought of as a down-and-in American-style barrier put option. It is written by the government and owned by the GSEs' shareholders.[5] A down-and-in put option knocks in—that is, becomes exercisable—when the price of the underlying asset hits a predetermined price barrier from above. When the barrier is hit, the holder of the option has the right (but not the obligation) to sell the underlying asset within a set time period at a predetermined price (the strike price) to the option writer. Barrier options may be monitored—that is, the market price compared to the barrier price—continuously or at discrete intervals. A barrier option is said to be monitored daily if the price of the underlying asset is checked against the barrier only once a day (rather than continuously).

The value of the underlying asset is the present value of the dividend stream accruing to the owners of GSE stock under the current regime of government sponsorship. That is, GSE shareholders own a portfolio composed a claim on the dividend stream—the equity claim—and a down-and-in put option on this claim. The value of the underlying asset is not observable because the recorded stock price is the sum of the price of the underlying asset and the value of the option (the option premium).

The underlying asset on which the put option is written is the (unobservable) present value of the dividend stream. Nevertheless, the strike price of the option may be related to the value of the entire portfolio—that is, the observed stock price—rather than the value of the underlying asset alone. This is because the investor's maximum potential loss is the value of the entire portfolio, rather than merely the equity claim. While it might be reasonable to think of the strike price being related to the observed stock price, continuous adjustment of the strike price to the stock price would render the put option worthless. Thus, we assume that, should the option not have knocked in on a given trading day, the government adjusts the strike price of the option immediately after the market close to the closing stock price and extends the time to expiration of the option by another day. But if the option has knocked in—that is, if the (unobservable) present value of the dividend streams touched the barrier—then there is no adjustment to the strike price or the time to expiration. In this case, the shareholders have the right (but not the obligation) to redeem their shares with the government within perhaps 90 calendar days (starting with the next calendar day) at the closing price of the day before the price of the underlying asset touched the barrier. (The 90-day period implies that, should the option not knock in, the time to expiration is reset at 92 days at the end of the trading day.)

With such a pricing rule—assumed to be known to all investors—the daily return on GSE shares consists of two parts. First, there is the return on the underlying asset—that is, the return on the present value of the dividend stream. Second, there is the return on the embedded barrier option due to the change in the value of the underlying asset and, should the option not have knocked in, the accompanying adjustment in the strike price. (Note that if the option does not knock in, the time to expiration remains unchanged at 92 calendar days.)

Chart 1 shows the return on a portfolio consisting of a stock—the equity claim—and a barrier put option written on this stock for a trading day on which the option does not knock in.[6] The return on the equity claim—that is, changes in the market valuation of the present value of the dividend stream—is shown on the horizontal axis. The return on the portfolio—the return on the equity claim and the put option taken together—is convex in the return on the equity claim, as indicated by the solid circles. Note that, in keeping with our assumptions, the strike price of the barrier option is set at the sum of the (unobservable) price of the underlying asset and the option premium, and the time to expiration is constant (rather than decreasing by one calendar day).[7]

4. Dissecting the GSE Stock Return

In generating testable hypotheses about the existence of a put option in GSE stock we face the difficulty that the price of the underlying asset—the value of the equity claim—is not observable. To overcome this problem, we derive a relation between the market return and the stock return (inclusive of the embedded put) using the Sharpe-Lintner CAPM. Under the null hypothesis of no embedded option, the relation between the market return and the return on GSE stock is linear, subject to the condition that the Sharpe-Lintner CAPM is an adequate model for the return on the underlying asset. But if there is a put option embedded in the stock, then the relation between the market return and the observed return on GSE stock must be convex, as suggested by option theory. For now, we make no specific assumptions about the type of option embedded in GSE stock.

In order to link the return on GSE stock to the Sharpe-Lintner CAPM, we assume that the government insures—by means of option-writing—only the non-diversifiable risk (rather than the total risk) in the return on the equity claim. The idiosyncratic risk remains uninsured because it is diversifiable. What else might matter? A large literature explores additional risk factors that may be priced in stock returns. Chen, Roll, and Ross (1986) identify five priced economic factors in stock returns, including the interest-rate term spread, expected inflation, and unexpected inflation. Campbell (1996) investigates returns on twelve industry-based stock portfolios and several bond portfolios. He finds that finance and real estate stock returns are more negatively related to innovations in the term spread than any other stock portfolio but utilities. More importantly for Fannie Mae and Freddie Mac, Campbell (p. 335) finds that bond portfolio returns are more strongly affected by changes of the short-term interest rate and the term spread than by innovations in either the stock-market return, a proxy for returns on human capital, or the stock market's dividend yield (a proxy for the price of risk in financial markets). Because Fannie Mae and Freddie Mac essentially are large bond-fund managers, it therefore is important to control for interest-rate risk (the changes in both the level of rates and the slope of the yield curve) when attempting to explain their stock returns. We return to this issue in Section 5, where empirical implementation of the model is discussed.

We assume the uninsured return is independently and normally distributed with mean 0 and constant, finite variance. An example of idiosyncratic risk faced by government-sponsored enterprises is the uncertainty surrounding the privileges associated with their federal charters, the regulatory requirements to which they are subject, and the strictness with which these regulations are enforced (OFHEO, 2003). Some of the privileges are provisional agreements, such as the handling of daylight overdrafts in their accounts at the Federal Reserve (OFHEO, 2003); these agreements are subject to political influence from the Treasury Department and Congress. At the extreme, the Congress might revoke some or all of the privileges of Fannie Mae and Freddie Mac, possibly in response to corporate-governance issues at these institutions. Another conceivable idiosyncratic risk faced by GSE stockholders emanates from the demographics of the U.S. population and a potential decrease in the demand for housing (and thus mortgages).

The return on GSE stock beyond the manifestation of idiosyncratic risk, ε_t, is a weighted average of the insured return on the equity claim, r_t^e—that is, the return on the equity claim that covaries with undiversifiable risk factors—and the return on the put option, r_t^o. Thus, we can express the return on GSE stock, r_t^s, as:

(1) $$r_t^s = \lambda_{t-1} \cdot r_t^e + (1-\lambda_{t-1}) \cdot r_t^o + \varepsilon_t \ , \ 0 < \lambda_{t-1} < 1 ,$$

where $\lambda_{t-1} \equiv p_{t-1}^e / p_{t-1}^s$ is the previous period's fraction of the value of the equity claim, p_{t-1}^e, in the stock price, p_{t-1}^s.

For the excess stock return, $\tilde{r}_t^s$, we obtain:

(2) $$\tilde{r}_t^s = \lambda_{t-1} \cdot \tilde{r}_t^e + (1-\lambda_{t-1}) \cdot (r_t^o - r_t^f) + \varepsilon_t \ ,$$

where $\tilde{r}_t^s \equiv r_t^s - r_t^f$, $\tilde{r}_t^e \equiv r_t^e - r_t^f$, and r_t^f is the return on the risk-free asset.

The excess return on the equity claim is compensation for market risk—as suggested by the Sharpe-Lintner CAPM—and, possibly, interest rate risk, as discussed above (and in Section 5). Because the option is written on the equity claim, we can write the excess stock return as:

$$\text{(3)} \qquad \tilde{r}_t^s = \lambda_{t-1} \cdot \tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t) + (1-\lambda_{t-1}) \cdot r_t^o(\tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t) + r_t^f) - (1-\lambda_{t-1}) \cdot r_t^f + \varepsilon_t \ ,$$

where $\tilde{r}_t^m \equiv r_t^m - r_t^f$ is the market excess return, and $\boldsymbol{\varphi}_t$ is a vector of variables associated with interest-rate risk.

We do not propose a specific hypothesis about the relation between interest-rate factors and the return on GSE equity claims—a relation that might be linear or nonlinear. Hence, we have no benchmark relation between interest-rate risk factors and GSE stock returns that would allow us to discern the presence of an embedded put option. It is an entirely different matter for the influence of market risk on the return on GSE equity claims, however. We know from the Sharpe-Lintner CAPM that the relation between the excess return on the equity claim, $\tilde{r}_t^e$, and the market excess return, $\tilde{r}_t^m$ is linear, being determined by the CAPM beta. Thus, taking the first derivative of the excess stock return, $\tilde{r}_t^s$, with respect to the market excess return, $\tilde{r}_t^m$, leads to:

$$\text{(4)} \qquad \frac{\partial \tilde{r}_t^s}{\partial \tilde{r}_t^m} \equiv \lambda_{t-1} \frac{\partial \tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t)}{\partial \tilde{r}_t^m} + (1-\lambda_{t-1}) \frac{\partial r_t^o(\tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t))}{\partial \tilde{r}_t^e} \cdot \frac{\partial \tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t)}{\partial \tilde{r}_t^m}$$

$$= \lambda_{t-1} \cdot \beta(\boldsymbol{\varphi}_t) + (1-\lambda_{t-1}) \frac{\partial r_t^o(\tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t))}{\partial \tilde{r}_t^e} \cdot \beta(\boldsymbol{\varphi}_t)$$

$$\equiv \beta(\boldsymbol{\varphi}_t) \cdot [\lambda_{t-1} + \frac{\partial r_t^o(\tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t))}{\partial \tilde{r}_t^e} \cdot (1-\lambda_{t-1})] \ .$$

Equation (4) shows, that for a given portfolio composition (as indicated by λ_{t-1}), the put option dampens the return on the underlying asset and, for large negative returns on the equity claim, might even turn it into a positive portfolio return. This is because the first derivative of the option return on the excess return on the equity claim, $\partial r_t^o(\tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t))/\partial \tilde{r}_t^e$, is negative. Thus, so is the second derivative $\partial^2 r_t^o(\tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t))/\partial \tilde{r}_t^{e^2}$, as implied by the convexity of the option premium in the price of the underlying asset.

Equation (4) also shows that the relation between the excess return on GSE stock, $\tilde{r}_t^s$, and the market excess return, $\tilde{r}_t^m$, is a function of interest-rate factors. In other words, for a given initial fraction of the option premium in the stock price, $1-\lambda_{t-1}$, the impacts of market returns (on one hand) and interest rate changes (on the other hand) on the GSE stock return are nonadditive.

There is yet another important implication of Equation (4) for the nature of the GSE stock return:

$$(5) \qquad \frac{\partial^2 \tilde{r}_t^s}{\partial \tilde{r}_t^{m^2}} = \beta(\boldsymbol{\varphi}_t)\cdot(1-\lambda_{t-1})\frac{\partial^2 r_t^o(\tilde{r}_t^e(\tilde{r}_t^m, \boldsymbol{\varphi}_t))}{\partial \tilde{r}_t^{e^2}} < 0 \ .$$

The convexity in the return of the embedded put option translates into a convexity of the excess return on the stock. Put differently, for a given initial fraction of the option premium in the observed stock price, $1-\lambda_{t-1}$, the return on GSE stock is convex in the market excess return.

Chart 1 illustrates the preceding discussion. The alternative axis labels are denoted in parentheses. Assume that the value of the equity claim in GSE stock varies with the market only—that is, there is no interest-rate risk and no idiosyncratic risk. In such a situation, the return on GSE stock behaves as shown in Chart 1. The horizontal axis of Chart 1 shows the market return, while the vertical axis displays the return on the equity claim (diagonal line) and the return on the stock (traced out by solid circles). The return on the stock is the return on a portfolio that consists of the equity claim and a barrier put option of the type described in Section 3. (The diagonal line in the chart implies that the return on the equity claim varies one-to-one with the market return.) As the value of the equity claim approaches the boundary from above (but never crosses it) for very low returns, the positive return on the option dominates the negative return on the equity claim. In the upward sloping section of the dotted line, the relation between the GSE stock return and the market return is negative.

Finally, we have to make an assumption about the behavior of λ—the fraction of the value of the equity claim in the stock price. Note that the ratio $(1-\lambda)/\lambda$ is the fair value of the insurance provided by the guarantor (presumably the government) per one dollar of equity claim. Thus, a hypothesis about λ is a proposition about the behavior of the government as an insurer for GSE shareholders. It would be inconsistent to assume that λ is constant, since this would run counter to the concept of the government providing insurance. This is because, for λ to be constant, the return on the option must always equal the return on the equity claim and, hence, there would be no insurance. On the other hand, assuming that λ changes solely with market prices and is not controlled by the government is not a reasonable assumption either. This is because, without the government adjusting the portfolio composition, the fraction of the insurance premium provided by the government per dollar of GSE equity would vary over time devoid of a persuasive economic rationale.

In deriving a hypothesis about the government's insurance provision for GSE equity, we assume—for expositional purposes—that the value of the equity claim varies with insured factors only (rather than with idiosyncratic risk factors too). First, we hypothesize that λ is a stationary variable. A sufficient condition for this assumption to hold is that the integral of changes of λ over the excess returns on the equity claim, $\tilde{r}^e$, equals zero:

$$(6) \qquad 0 = \int_{\tilde{r}^e=-1}^{\tilde{r}^e=+\infty} d\lambda d\tilde{r}^e \ .$$

Note that the excess return on the equity claim includes drift or, synonymously, expected excess return.

Second, we hypothesize that the government, in order to bring about a stationary λ, adjusts the attributes of the embedded option such that for excess returns on the equity claim greater than the drift, $\tilde{r}_t^e > E(\tilde{r}^e)$, λ remains unchanged ($\lambda_t = \lambda_{t-1}$). Remember that an invariable λ implies that the return on the option equals the return on the equity claim or, in other words, that the effective delta of the return on the embedded option is unity. Also, this hypothesis implies

$$(7) \qquad 0 = \int_{\tilde{r}^e = E(\tilde{r}^e)}^{\tilde{r}^e = +\infty} d\lambda d\tilde{r}^e \; .$$

Whereas an invariant λ is a reasonable assumption for super-drift excess returns on the equity claim under the random-walk hypothesis, for sub-drift excess returns, the assumption would imply that the option provides no insurance. Recall that changes of λ for sub-drift returns must meet the following condition:

$$(8) \qquad 0 = \int_{\tilde{r}^e = -1}^{\tilde{r}^e = E(\tilde{r}^e)} d\lambda d\tilde{r}^e \; .$$

For condition (8) to hold for a varying λ, $d\lambda$ must be negative for at least one sub-drift excess return on the equity claim. Note that, for $d(1-\lambda) < 0$, the negative return on the embedded option is larger (in absolute value) than the negative return on the equity, exacerbating the loss to the investor. For $d(1-\lambda) > 0$, the (possibly negative) return on the option dampens the effect on the portfolio of the negative return of the equity claim; only then does the option provide insurance. Taken together, we assume that $1-\lambda$ initially decreases with sub-drift excess returns and then, for large negative returns, increases. In other words, we assume $1-\lambda$ to be a u-shaped function in the sub-drift returns on the equity claim.

Chart 2 incorporates the hypothesized government-provided insurance into the concept of the barrier put option outlined in Section 3. Within this option framework, the government can easily adjust λ by adjusting the barrier. For super-drift returns on the equity claim, the government adjusts the barrier upward such that λ remains unchanged. For small sub-drift returns, the government adjusts the barrier downward by an amount sufficient to cause $1-\lambda$ to decrease. For large negative returns, for instance, the government might adjust the barrier by no more than it does for small returns. This causes $1-\lambda$ to increase. The solid circles in Chart 2 indicate the return on the portfolio (consisting of the equity claim and a barrier put option) as a function of the return on the equity claim. For positive returns on the equity claim—the case in which λ is constant—the return on the equity claim and the portfolio are equal; thus, they are located on the diagonal line. For small negative returns on the equity claim—the case in which $1-\lambda$ decreases—the percentage loss to the portfolio exceeds the percentage loss on the equity claim. Finally, for large negative returns, the quantity $1-\lambda$ increases. In this case, the government provides insurance by dampening the negative return on the equity claim via a comparatively smaller negative or even a positive return on the option.

Note that a stationary λ implies that the insurance provided by the government to the GSE shareholders covers only catastrophic, but not atrophic losses. The insurance provided by the government provides safety against large and sudden declines in the value of the equity claim but not against its gradual erosion over time.

Taken together, the foregoing analysis generates two hypotheses that, in modified form, can be tested empirically. The first hypothesis follows from Equation (5) and concerns the convexity of negative GSE stock returns that result from the insurance provided by the government through an embedded put option in GSE stock:

Hypothesis 1: The negative excess return on GSE stock is strictly convex in the market excess return.

The second hypothesis concerns the additivity of the influence on the GSE excess return of the market return and interest-rate factors. As shown in Equation (4), the relation between the GSE excess stock return and the market excess return is a function of interest-rate factors, which implies:

Hypothesis 2: The influences of the market return and of interest-rate factors on the excess return on GSE stock are nonadditive.

The next section outlines our econometric methodology. This methodology allows us to test the nonlinearities implied in Hypotheses 1 and 2, which manifest themselves in non-vanishing second derivatives (Hypothesis 1) and cross-derivatives (Hypothesis 2).

5. Empirical Methodology

We begin our empirical search for evidence of a put option in the returns on GSE stocks with a linear relation between the excess return on the GSE stock and the excess return on the market—as suggested by the Sharpe-Lintner CAPM:

$$\tilde{r}_t^s = \beta \cdot \tilde{r}_t^m + \varepsilon_t \ , \quad (9)$$

We extend this linear model in three important ways, as motivated by our theoretical analysis in Section 4. First, we add two interest-rate factors that potentially bear on the stock price of Fannie Mae and Freddie Mac. These two interest-rate factors are (1) the change of the yield to maturity on the short end of the Treasury yield curve and (2) the change in the Treasury term spread, the difference between a long-term yield and a short-term yield. Second, we allow the relations between the excess GSE stock return and the market excess return and the interest-rate factors to be nonlinear. In other words, we allow for non-vanishing second derivatives of the excess stock return with respect to any or all of these three variables. The reason for accommodating non-vanishing second derivatives lies in Hypothesis 1, which states that the relation between the excess GSE stock return and the market excess return is convex. Third, we allow for non-vanishing cross-derivatives or, put differently, we do not impose additivity of the influences of the three right-hand side variables on the GSE excess stock return. This means that we allow the relations between the GSE excess stock return and any of the three variables to covary with any other variable. Allowing for non-vanishing cross-derivatives is motivated by Hypothesis 2, which says that the interest-rate factors bear on the relation between the GSE excess stock return and the market excess return.

We arrive at the following nonlinear empirical model:

(10) $$y_t = f(\mathbf{z_t}) + \varepsilon_t \ ,$$

where $y_t \equiv \tilde{r}_t^s$ is the excess log return on GSE stock, as defined above, and ε is a normally distributed error term with mean 0 and constant, finite variance, σ^2. The vector $\mathbf{z_t}$ comprises the time t observations of the daily excess return of the market portfolio, $\tilde{r}_t^m$, the daily change of the short rate, $\varphi_{1,t}$, the daily change of the term spread, $\varphi_{2,t}$, and a constant. The excess returns on Fannie Mae or Freddie Mac stock, $\tilde{r}_t^s$, are defined as the difference between the respective daily logarithmic stock return and the logarithmic return on an investment in the overnight eurodollar market. Similarly, the daily market excess return is the difference between the logarithmic return on the value-weighted CRSP stock market index and the log return on an overnight eurodollar investment. We implement the short rate of the Treasury yield curve with the constant-maturity 3-month T-bill yield, and the term spread we gauge by the difference between the constant-maturity 10-year T-note yield and the constant-maturity 3-month T-bill yield. See Appendix A for details on the definition of the variables and our data sources.

We estimate model (10) using locally weighted regression (LOESS), as developed by Cleveland and Devlin (1988). LOESS is a multi-dimensional smoother that can accommodate not only non-vanishing second derivatives of the explanatory variables, but also non-vanishing cross-derivatives. In other words, LOESS can accommodate arbitrarily smooth influences of the explanatory variables without imposing the constraint that these influences be linear or additive. As shown by Cleveland, Devlin, and Grosse (1988), LOESS can reproduce peaks and is insensitive to asymmetrically distributed data. What is more, LOESS has many desirable statistical properties, as reviewed in Hastie and Tibshirani (1990) and Goodall (1990). More recently, Fan (1992) has shown that locally linear regression smoothers, such as LOESS, have high asymptotic efficiency. Unlike many other smoothers, locally linear regression is not liable to "boundary effects" that might arise from the lack of a neighborhood on one side of a given data point. For details on the econometric method, see Appendix B.

6. Model Selection and Analysis of Variance

We approach the testing of our hypotheses as a model-selection problem. Starting from the unconstrained model (10), we impose restrictions and test their significance in an analysis of variance. For an analysis of variance to be valid, the fitted values $\hat{\mathbf{y}}$ of the unrestricted model must be unbiased. Under the null hypothesis, the fitted values of the restricted model also are unbiased (Hastie and Tibshirani, 1990).

We start by determining a specification of model (10) that can be assumed to deliver unbiased estimates of the dependent variable; this specification then will serve as the unrestricted model in the analysis of variance. In the LOESS estimation technique, the specification choice is a problem of selecting the smoothing parameter, g—the fraction of sample observations included in the estimation of the functional form around a given data point. The larger the smoother parameter, $0 < g \leq 1$, the smoother is this estimated functional form, possibly at the expense of a bias in the fitted values.

Cross-validation, a commonly used technique for determining the smoothing parameter (or bandwidth, in kernel estimation) does not offer a solution to our specification problem. This is because cross-validation minimizes the average mean squared error, deliberately trading off some variance for a bias (Li, 1990; Andrews, 1991). Instead, we employ the *M*-plot method suggested by Cleveland and Devlin (1988). This technique, which is derived from Mallows' (1973) C_P criterion and is detailed in Appendix B, offers a graphical exposition of the contributions of bias and variance to the mean squared error of the fitted values. Most importantly, the *M*-plot method is a way of choosing the smoothing parameter that entails the smallest variance subject to not generating a statistically significant bias in the fitted values. To this end, the *M*-plot method starts by estimating the model with a smoothing parameter that is sufficiently small for the bias to be negligible. The smoothing parameter then is increased in small steps. The largest smoothing parameter that does not generate a statistically significant bias is the model of choice.

Before presenting the *M*-plots and the results of the hypothesis tests from the analysis of variance, we must address the question of normality in the GSE stock returns. It is well known that daily returns of individual stocks are leptokurtic (that is, display excess kurtosis) and may be skewed (Campbell, Lo, and MacKinlay, 1997). Charts 3 and 4 show the respective empirical probability densities for Fannie Mae and Freddie Mac daily logarithmic excess stock returns during the period May 20, 1991, to December 31, 2002. This is the time period we use in our empirical analysis. The thick line represents a kernel estimate of the probability density while the thin line shows the probability density of the normal distribution based on the respective means and sample standard deviations. A visual comparison of the kernel density estimate with the normal implied by the sample estimates of the moments suggests that the normal is only a rough approximation to the actual return distribution. Both skewness and kurtosis are statistically significant, although the values for skewness (Fannie Mae: 0.125; Freddie Mac: 0.261) imply only a mild deviation from symmetry. Kon (1984) has shown that leptokurtic individual stock returns can be modeled as being generated by mixed normal distributions. While using the *M*-plot method of choosing the smoothing parameter, we maintain the assumption of normally distributed error terms of the regression model as a first-order approximation. We also assume normality for the analysis of variance. However, we also provide a bootstrapped analysis of variance that allows for heteroskedastic error terms as might be generated by mixed zero-mean normal distributions.

Charts 5 and 6 show *M*-plots for Fannie Mae and Freddie Mac, respectively. The diagonal line in an *M*-plot signifies the contribution of variance to the estimated mean squared error, shown on the horizontal axis as the equivalent number of parameters of the fit. The vertical axis displays the *M*-statistic, which is the sum of the respective contributions of variance and bias. For a sufficiently small smoothing parameter, g, the bias of the fit is negligible, delivering nearly unbiased estimates of the variance, σ^2. Cleveland and Devlin (1988) argue that this value for the smoothing parameter, g, is usually in the range of 0.2 to 0.4, from which we chose the midpoint. The rightmost symbol in the *M*-plot indicates the *M*-statistic that is associated with $g = 0.3$; the estimated bias is zero, by definition. As the smoothing parameter increases from 0.3 to 1 (in steps of 0.05), the contribution of variance decreases and confidence bounds for the bias widen. (For comparison, we also provide the *M*-statistic for the linear model $y_t = \mathbf{z}_t'\boldsymbol{\beta} + \varepsilon_t$, which is estimated with ordinary least squares and identified in the charts by the □-symbol.) Following Cleveland and Devlin, we choose the largest smoothing parameter that shows no statistically significant bias; these parameter values are 0.9 for Fannie Mae and 0.95 for Freddie Mac. These specifications serve as the unrestricted models in the analysis of variance.

First, we jointly test Hypotheses 1 and 2. Recall that Hypothesis 1 states that the negative excess return on GSE stock is strictly convex in the market excess return. Hypothesis 2 says that the influence of the market and of the interest rate factors are nonadditive. In testing these hypotheses jointly, we impose a linearity restriction on model (10), which leads to the following semiparametric model:

(11) $$y_t = \beta \cdot x_t + f(\tilde{\mathbf{z}}_\mathbf{t}) + \varepsilon_t \; .$$

In model (11), the scalar x_t—the parametric component of model (11)—is the time t observation of the market excess return, while the vector $\tilde{\mathbf{z}}_\mathbf{t}$—the nonparametric component—comprises all other explanatory variables included in $\mathbf{z}_\mathbf{t}$ as defined in model (10), including a vector of ones. The non-parametric component of model (11), $f(\tilde{\mathbf{z}}_\mathbf{t})$, is estimated using LOESS, whereas the parametric component is estimated using ordinary least squares. For details on the estimation technique see Appendix B.

The null hypothesis in the joint test of Hypotheses 1 and 2 is that there is additivity and no convexity in GSE stock returns. Because this null hypothesis is not strictly complementary to the situation in which Hypotheses 1 and 2 hold jointly, we will add (in the next section) a graphical exposition of the regression results to the analysis of variance.

Second, we test Hypothesis 2 in isolation by imposing on model (10) the restriction that the influences of the market and of the interest rate factors are additive. The additivity restriction converts model (10) into the following generalized additive model:

(12) $$y_t = f_1(x_t) + f_2(\tilde{\mathbf{z}}_t) + \varepsilon_t \ .$$

Unlike the semi-parametric model (11), equation (12) does not impose linearity on the influence of the market excess return on the dependent variable. But, like the semi-parametric model, the influences of the market excess return, x_t, and the joint influences of the other right-hand side variables, $\tilde{\mathbf{z}}_t$, are restricted to be additive. Model (12) is estimated using LOESS with the backfitting algorithm developed by Hastie and Tibshirani (1986). For details on estimating model (12), see Appendix B.

The analysis of variance rests on an *F*-statistic that is derived from a two-moment χ^2-approximation (Cleveland and Devin, 1988); this *F*-statistic is detailed in Appendix B. Table 1 shows the results of the analysis of variance for the two hypothesis tests, along with the results of tests on other restrictions of interest. Based on this analysis of variance, we can reject both the null of a linear relation between GSE excess stock returns and market excess returns and of additivity of the market and interest-rate factors. Furthermore, we can reject the null hypothesis that the interest-rate factor has no bearing on the stock returns of Fannie Mae or Freddie Mac. Finally, we can reject the hypothesis that the linear model, $y_t = \mathbf{z}_t'\boldsymbol{\beta} + \varepsilon_t$, delivers an unbiased fit for GSE stock returns.

Table 1 also provides results from an analysis of variance based on bootstrap percentiles, which is motivated as follows. For an unbiased smooth $\hat{\mathbf{y}} = \mathbf{S} \cdot \mathbf{y}$, an unbiased estimator of σ^2 is

(13) $$\hat{\sigma}^2 = \frac{(\hat{\mathbf{y}} - \mathbf{y})'(\hat{\mathbf{y}} - \mathbf{y})}{df^{err}} \ ,$$

where $df^{err} \equiv T - \mathrm{tr}(2\mathbf{S} - \mathbf{S}\mathbf{S}')$ is the error degrees of freedom and T is the number of observations (Hastie and Tibshirani, 1990). The difference in variance between the unrestricted model (10) and the applicable restricted model can be bootstrapped using the biased variance estimator $\hat{\sigma}_b^2 = (\hat{\mathbf{y}} - \mathbf{y})'(\hat{\mathbf{y}} - \mathbf{y})/T$ (Efron and Tibshirani, 1993). Because this biased estimator is the same for any normal distribution, the bootstrapping technique is applicable even when the error terms are heteroskedastic. The bootstrapping approach does not impose the condition that each pair of residuals—consisting of a residual from the unrestricted model and a corresponding residual from the restricted model—is generated by the same zero-mean normal distribution. With heteroskedastic error terms, the analysis of variance ceases to be a test of the equality of variances across models and becomes a test of the equality of the weighted sum of variances.

The percentile bootstrap intervals shown in Table 1 confirm the results from the traditional analysis of variance. We can reject the restricted, semi-parametric and generalized additive models in favor of the nonparametric model.

7. Graphical Exposition

Charts 7 and 8 offer a visualization of the LOESS estimates of the unrestricted, non-parametric model (10). For each of the three explanatory variables—the market excess return, the change of the short rate and the change of the term spread—the regression results are presented in a set of 9 conditioning plots, as suggested by Cleveland and Devlin (1988). Conditioning plots display the estimated partial impact of a single explanatory variable on the dependent variable. All other explanatory variables are pegged at chosen levels. Because the intercept is not identified in LOESS estimates, only *changes* of the displayed partial impact (rather than the level itself) can be interpreted in an economically meaningful manner. The variable that is allowed to change in a conditioning plot—shown on the horizontal axis—adopts only values that are actually observed in the neighborhood of the values at which the pegged explanatory variables are set. Specifically, when we peg a variable to its median negative (positive) value, only observations for which this variable adopts nonpositive (nonnegative) values are included in the conditioning plot. Similarly, when we peg a variable at zero, only observations for which this variable lies within the closed interval of the median negative value and the median positive value are included in the conditioning plot. From the set of observations chosen this way, we discard the ten most extreme ones (on either side) of the particular variable in the conditioning plot before evaluating the estimated functional form for the displayed range of values. The dashed lines denote 90 percent point-wise confidence bounds, as derived by Cleveland and Devlin. The "whiskers" at the bottom of each chart indicate the dispersion of the observations on the horizontal axis. For Panels B and C, the whiskers take on the shape of a frequency distribution because changes of the short rate and the yield spread are recorded in discrete increments.

Panel A of Chart 7 shows the partial impact of the market excess return on the excess return of Fannie Mae stock. The market excess return is varied on the horizontal axis and the other two explanatory variables—the changes of the short rate and the term spread—are varied across plots. For instance, in the northwestern plot, the change of the short rate is held at its median negative value, and so is the change of the term spread. In the center plot, these two explanatory variables are held at zero, and in the southeastern plot, they are held at their positive median values. Thus, the influence on the excess return on Fannie Mae stock of changes in the short rate and the term spread can be read from the changes of the location and the shape of the displayed functional form across conditioning plots. Furthermore, the influence on the excess stock return of Fannie Mae of the two interest rate factors is visible in Panels B and C. These panels show that, all else being equal, the excess return on Fannie Mae stock is adversely affected by an increase in the short rate (Panel B) and a steepening of the yield curve (Panel C). These results are consistent with Campbell's (1996) findings for bond portfolios and finance and real estate stock returns.

Hence, the northwestern conditioning plot in Panel A shows the most favorable case for the value of the equity claim in Fannie Mae stock—the short rate drops and the term spread lessens. Conversely, the southeastern plot shows the least favorable case—the short rate rises and so does the term spread. Our theoretical model suggests that for negative market excess returns, in the case where the absolute value of the negative insured return on the equity claim is largest, the convexity of the Fannie Mae excess stock return is the most pronounced (southeastern plot). On the other hand, in the most favorable case, where the impact on the equity claim of the negative market excess return is dampened by a favorable change of the interest rate environment, the convexity is predicted to be the least pronounced (northwestern plot). Indeed, the set of conditioning plots displayed in Panel A have this property in that the convexity of the Fannie Mae excess returns in relation to the market excess return is more pronounced in the southeastern plot than in the northwestern plot.

Conceptually, the center plot of Panel A is closely related to Chart 2, which displays the return on a portfolio consisting of an equity claim and a long position in a down-and-in barrier option written on this claim. If we assume, for simplicity, that the return on the equity claim varies one-to-one with the market return (as indicated by the axis label in parentheses), then the vertical axis in Chart 2 measures the GSE stock return (again, as indicated by the axis label in parentheses). The estimated functional form shown in the center plot of Chart 7 displays three critical characteristics of the GSE stock return predicted by the theoretical model and shown in Chart 2. First, for positive market excess returns, the relation between the market excess return and the GSE excess return is linear. For comparatively small negative market excess returns, the absolute value of the negative GSE excess return is larger than it is for positive market excess returns of the same magnitude. In other words, for comparatively small negative market excess returns, the estimated functional form of the GSE excess return is steeper in the market excess return than it is for positive market excess returns. Finally, for large negative market excess returns, the GSE excess return is convex in the market excess return.

Chart 8 shows the conditioning plots for Freddie Mac. These plots look very similar to those of Fannie Mae. Recall that the smoothing parameter for Freddie Mac is somewhat larger than the one for Fannie Mae (0.95 for Freddie Mac compared with 0.9 for Fannie Mae), but otherwise the approach is identical.

8. Conclusion

Fannie Mae and Freddie Mac are government-sponsored enterprises with publicly traded equity. Although these companies hold government-issued charters, their securities are not legally backed by the full faith and credit of the United States government. Yet, investors and rating agencies seem to believe that the U.S. Government would bail out Fannie or Freddie if they became distressed.

We provided theoretical motivation and empirical evidence for a conjectural guarantee in the stock returns of Fannie Mae and Freddie Mac. We showed that stock that contains an option on returning the shares at a given price to the issuer—the government, in this case—show pronounced nonlinearity (convexity) in the sensitivity of its return to market return. We uncovered this convexity in daily GSE stock returns using non-parametric regression techniques. Our findings are consistent with a government guarantee in GSE stock against catastrophic losses but not against atrophic losses.

Our findings can be interpreted in two, non-mutually exclusive ways. One view on the conjectural guarantee in GSE stock is the case of being too big to fail. As mentioned, as of June 30, 2003, Fannie Mae and Freddie Mac taken together held about $1.5 trillion of assets and guaranteed against default another $2 trillion. At year-end 2001, the notional amount of financial derivatives outstanding of Fannie Mae and Freddie Mac taken together ran at $1.6 trillion. Financial failure of one or both of these institutions would pose considerable risk to the U.S. financial system (Office of Federal Housing Enterprise Oversight, 2003). It is not surprising then, that investors perceive the liabilities of the GESs as backed by the full faith and credit of the U.S. government, even though this is not legally the case. As shown by O'Hara and Shaw (1990), the wealth effect to investors of governmental too-big-to fail guarantees can be substantial.

Another way of looking at the conjectural guarantee embedded in GSE stock is that it serves Allen and Gale (1997). In the model of Allen and Gale, the government sponsors the accumulation of a safe asset as an instrument of intertemporal risk-sharing.

[1] The federal regulator of Fannie Mae and Freddie Mac, the Office of Federal Housing Enterprise Oversight (OFHEO), provides links to all of the public disclosures of both enterprises on its website, <http://www.ofheo.gov>.

[2] See, for instance, Standard and Poor's at <http://www.standardandpoors.com>.

[3] For more background on the housing GSEs, see Frame and Wall (2002).

[4] See Congressional Budget Office (2001) for more background information and an estimate of the federal subsidies enjoyed by the housing GSEs.

[5] For a formal treatment of barrier options, see Rubinstein and Reiner (1991); for intuition, see Taleb (1997).

[6] The down-and-in barrier put option has American-style exercise, 92 calendar days to expiration and a barrier at $30. We adjusted for daily monitoring using the algorithm suggested by Broadie, Glasserman, and Kou (1997). We set the volatility of the underlying asset at 30 percent, the continuously compounded risk-free rate (per annum) at 3 percent, and the annual dividend payment (which is assumed to be compounded continuously) at $1.80. We assumed 250 trading days per year. We calculated the option premium using a trinomial tree with 1,500 steps.

[7] We set the strike price at the sum of the price of the underlying asset and the option premium; starting from the price of the underlying asset, we used an iteration procedure to determine the other two values.

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Appendix A: Data Sources and Description of Variables

All observations are daily, starting on May 20, 1991, and ending on December 31, 2002. May 20, 1991, was the first day for which the overnight eurodollar rate is available from Bloomberg. The logarithmic return on an overnight eurodollar investment serves as the daily return on the risk-free asset. We measure the market return as the logarithmic return on the CRSP value-weighted stock market index; this index comprises all issues covered by the CRSP database, excluding American Depository Receipts. The value-weighting for both the CRSP stock market index and the financial services index uses weights based on the previous trading day's market capitalization relative to total market capitalization of all stocks included in the respective index. The employed Treasury yields, which are recorded in percent, comprise the constant-maturity 3-month Treasury bill yield and the constant-maturity 10-year Treasury note yield; these data are from the Federal Reserve Board release H.15 via Haver. We define the term spread as the difference between the 10-year and the 3-month yields. All stock market data are from CRSP®, Center for Research in Security Prices, Graduate School of Business, The University of Chicago, <http://crsp.uchicago.edu>. Used with permission. All rights reserved.

Appendix B: Econometric Methodology

We estimate the nonparametric model

(B1) $$y_t = f(\mathbf{z}_t) + \varepsilon_t \ ,$$

where y_t denotes an observation of the dependent variable at time t, the vector $\mathbf{z}_t$ comprises the observations of the explanatory variables at time t, and ε_t is an independently and normally distributed error term with mean 0 and constant, finite variance σ^2. The dependent variable is the daily excess stock return of Fannie Mae and Freddie Mac, respectively. The excess return is defined as the difference between the respective logarithmic stock return and the log return on the risk-free asset. The explanatory variables comprise a vector of ones, the market excess return, the difference between the constant-maturity 3-month Treasury bill yield at times t and t-1, and the difference between the time t and time t-1 term spreads. The market excess return equals the difference between the CRSP value-weighted logarithmic stock market index return and the log return on the risk-free asset. The term spread is defined as the difference between the constant-maturity yields of the 10-year Treasury note and the constant-maturity 3-month Treasury bill. For details on the definition of the variables and the data sources see Appendix A.

We estimate model (B1) using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988). LOESS estimates the functional form in each observation by defining a neighborhood comprising the fraction g of the data points in the population; this fraction of data points is called the smoothing parameter. The data points to be included in the neighborhood are selected and weighted based on their respective Euclidean distance to the observation in question. We employ a tri-cube weight function, as detailed in Cleveland and Devlin.

LOESS smoothes the vector of observations of the dependent variable vector, $\mathbf{y}$, on the matrix of observations of the explanatory variables, $\mathbf{Z}$. The resulting smoother matrix, $\mathbf{S}$, establishes a linear relationship between $\mathbf{y}$ and the estimate $\hat{\mathbf{y}}$:

(B2) $$\hat{\mathbf{y}} = \mathbf{S} \cdot \mathbf{y} \ .$$

Given that the smooth $\hat{\mathbf{y}} = \mathbf{S} \cdot \mathbf{y}$ is an unbiased estimate of $\mathbf{y}$, an unbiased estimator of σ^2 is

(B3) $$\hat{\sigma}^2 = \frac{(\hat{\mathbf{y}} - \mathbf{y})'(\hat{\mathbf{y}} - \mathbf{y})}{df^{err}} \ ,$$

where $df^{err} \equiv T - \mathrm{tr}(2\mathbf{S} - \mathbf{SS'})$ is the error degrees of freedom and T is the number of observations (Hastie and Tibshirani, 1990). We will employ property (B3) to calculate nonparametric confidence intervals from bootstrap percentiles for the difference in variance between the unrestricted model (B1) and restricted models discussed below, using biased variance estimators (Efron and Tibshirani, 1993). This bootstrapping technique rests on the sum of pair-wise differences of the squared residuals without imposing the condition that each pair is generated by the same zero-mean normal distribution.

The regression results are presented in conditioning plots as introduced by Cleveland and Devlin (1988). Conditioning plots display the estimated partial impact of a chosen explanatory variable, with all other explanatory variables pegged to chosen constants. Because the intercept is not identified in this type of regression, only *changes* in the displayed partial impact (rather than the level itself) can be interpreted in an economically meaningful manner. The variable that is varied in a conditioning plot adopts only values that are actually observed in the neighborhood of the values at which the pegged explanatory variables are set. Specifically, when we peg a variable to its median negative (positive) value, only observations for which this variable adopts nonpositive (nonnegative) values are included in the conditioning plot. Similarly, when we peg a variable to zero, only observations for which this variable lies within the closed interval of the median negative value and the median positive value are included in the conditioning plot. From the thus chosen set of observations, we discard the ten most extreme observations (on either side) of the variable varied in the conditioning plot before evaluating the estimated functional form for the displayed range of values. We use the linearity property from (B2) to derive confidence intervals for the partial impact on the dependent variable displayed in the conditioning plots, as suggested by Cleveland and Devlin (1988).

In an analysis of variance, we also estimate two restricted versions of model of (B1). One of the restricted regression equations is the semi-parametric model

(B4) $$y_t = \beta \cdot x_t + f(\tilde{\mathbf{z}}_t) + \varepsilon_t \ ,$$

where the scalar x_t—the parametric component—is the time t observation of the market excess return, and the vector $\tilde{\mathbf{z}}_t$—the nonparametric component—comprises all other explanatory variables included in $\mathbf{z}_t$ as defined in equation (B1), inclusive of the intercept.

We estimate model (B4) in three steps, following Speckman (1988). In the first step, we use LOESS to smooth the vector of observations of the dependent variable, $\mathbf{y}$, on the matrix of observations of the explanatory variables contained in the nonparametric part, $\tilde{\mathbf{Z}}$. The resulting smoother matrix, $\mathbf{S}_{\mathrm{R}}$, establishes a linear relationship between $\mathbf{y}$ and the estimate $\hat{\mathbf{y}}$:

(B5) $$\hat{\mathbf{y}}_{\mathrm{R}} = \mathbf{S}_{\mathrm{R}} \cdot \mathbf{y} \ .$$

In the second step, we "purge" the dependent variable and the explanatory variables of the parametric component from the influence of the explanatory variables comprised in the nonparametric component:

(B6a) $\tilde{\mathbf{y}} = (\mathbf{I} - \mathbf{S}_\mathrm{R}) \cdot \mathbf{y}$

(B6b) $\tilde{\mathbf{X}} = (\mathbf{I} - \mathbf{S}_\mathrm{R}) \cdot \mathbf{X}$,

where $\mathbf{I}$ is the identity matrix.

In the third step, we estimate the parameter β using ordinary least squares:

(B7) $\hat{\beta} = (\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^{-1} \cdot \tilde{\mathbf{X}}'\tilde{\mathbf{y}}$.

As Speckman (1988) has shown, the bias of the estimator $\hat{\beta}$ is asymptotically negligible for sufficiently low values of the smoothing parameter, g .

The estimated impact of the explanatory variables in the semi-parametric model is

(B8) $\hat{\mathbf{f}} = \mathbf{S}_\mathrm{R} \cdot (\mathbf{y} - \mathbf{x} \cdot \hat{\boldsymbol{\beta}})$.

Thus, we can write for the estimated vector of the dependent variable:

(B9) $\hat{\hat{\mathbf{y}}} = \mathbf{x} \cdot \hat{\boldsymbol{\beta}} + \hat{\mathbf{f}}$.

It is straightforward to show that $\hat{\hat{\mathbf{y}}}$ is a linear function in $\mathbf{y}$:

(B10a) $\hat{\hat{\mathbf{y}}} = \mathbf{L} \cdot \mathbf{y}$,

where

(B10b) $\mathbf{L}=\mathbf{X}(\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}'(\mathbf{I} - \mathbf{S}_\mathrm{R})+\mathbf{S}_\mathrm{F}$

(B10c) $\mathbf{S}_\mathrm{F}=\mathbf{S}_\mathrm{R}[\mathbf{I} - \mathbf{X}(\tilde{\mathbf{X}}'\tilde{\mathbf{X}})^{-1}\tilde{\mathbf{X}}'(\mathbf{I} - \mathbf{S}_\mathrm{R})]$.

Another restricted version of regression model (B1) is the additive regression equation

(B11) $y_t = f_1(x_t) + f_2(\tilde{\mathbf{z}}_t) + \varepsilon_t$.

Unlike the semi-parametric model (B4), equation (B11) does not impose linearity on the influence of the market excess return on the dependent variable. But, like in the semi-parametric model, the influences of the market excess return, x_t, and the joint influences of the other right-hand side variables, $\tilde{\mathbf{z}}_t$, are restricted to be additive.

We estimate model (B10) using the backfitting algorithm suggested by Hastie and Tibshirani (1986). Backfitting consists of alternating the steps

(B12a) $$\mathbf{f}_1^{(m)} = \mathbf{S}_1^{(m)}(\mathbf{y} - \mathbf{f}_2^{(m-1)})$$

(B12b) $$\mathbf{f}_2^{(m)} = \mathbf{S}_2^{(m)}(\mathbf{y} - \mathbf{f}_1^{(m)}) \ ,$$

where $m \geq 1$ indicates the stage of the iteration procedure and $\mathbf{S}_1$ and $\mathbf{S}_1$ are the corresponding LOESS smoother matrices for the partial influences of $\mathbf{x}$ and $\mathbf{Z}$, respectively. We start out by smoothing $\mathbf{y}$ on $\mathbf{x}$ (and a vector of ones). The smoothing delivers fitted values for $\mathbf{y}$, $\mathbf{f}_1^{(0)}$. We subtract $\mathbf{f}_1^{(0)}$ from $\mathbf{y}$ and smooth this difference on $\tilde{\mathbf{Z}}$ (which includes a vector of ones), resulting in $\mathbf{f}_2^{(1)}$. We keep alternating the steps (B12a,b) until the vectors of fitted values, $\mathbf{f}_1^{(m)}$ and $\mathbf{f}_2^{(m)}$, stop changing. For the smoother matrix, we can write:

(B13) $$\hat{\mathbf{y}} = \mathbf{S} \cdot \mathbf{y} \equiv (\mathbf{S}_1 + \mathbf{S}_2) \cdot \mathbf{y} \ ,$$

where $\mathbf{S}_1$ and $\mathbf{S}_1$ the partial smoother matrices obtained in the last round of the iteration procedure.

Following Cleveland and Devlin (1988), the *F*-statistic for testing the statistical significance of the restriction imposed in models (B4) or (B11) over model (B1)—under the assumption of normality and the unrestricted model (B1) offering an unbiased estimate (B3)—reads

(B14) $$\hat{F}=\frac{(\mathbf{y}'\mathbf{R}_{\mathrm{L}}\mathbf{y}-\mathbf{y}'\mathbf{R}_{\mathrm{S}}\mathbf{y})/v_1}{(\mathbf{y}'\mathbf{R}_{\mathrm{S}}\mathbf{y})/\delta_1} ,$$

where $\mathbf{R}_{\mathrm{L}} \equiv (\mathbf{I}-\mathbf{L})\cdot(\mathbf{I}-\mathbf{L})'$, $\mathbf{R}_{\mathrm{S}} \equiv (\mathbf{I}-\mathbf{S})\cdot(\mathbf{I}-\mathbf{S})'$, $v_1 = \mathrm{tr}(\mathbf{R}_{\mathrm{L}}-\mathbf{R}_{\mathrm{S}})$, and $\delta_1 = \mathrm{tr}\,\mathbf{R}_{\mathrm{S}}$. The test statistic $\hat{F}$ is approximated by an *F*-distribution with v_1^2/v_2 numerator and δ_1^2/δ_2 denominator degrees of freedom, where $v_2 = \mathrm{tr}(\mathbf{R}_{\mathrm{L}}-\mathbf{R}_{\mathrm{S}})^2$ and $\delta_2 = \mathrm{tr}\,\mathbf{R}_{\mathrm{S}}{}^2$.

Note that the analysis of variance (B13) can easily be extended to the linearized version of the nonparametric model (B1):

(B15) $$y_t = \mathbf{z}_t{}'\boldsymbol{\beta} + \varepsilon_t .$$

The ordinary least squares equivalent to the smoother matrix $\mathbf{S}$ reads $\mathbf{Z}\cdot(\mathbf{Z}'\mathbf{Z})^{-1}\cdot\mathbf{Z}'$. We used this "smoother matrix" in the analysis of variance of Table 1 when testing the nonparametric model (B1) against the linear model (B15).

For model selection, we use *M*-plots, as developed by Cleveland and Devlin (1988). *M*-plots offer a graphical portrayal of the trade-off between the contributions of variance and bias to the mean squared error as the smoothing parameter, g, changes. The expected mean squared error summed over all observations and normalized by the variance, σ^2, reads

(B16) $$M_g = \frac{E(\mathbf{y}'\mathbf{R}_g\mathbf{y})}{\sigma^2} ,$$

where the subscript g indicates the chosen smoothing parameter. For a sufficiently small smoothing parameter—let us say, f—the bias of the vector of the fitted values, $\hat{\mathbf{y}}$, is negligible, resulting in a nearly unbiased estimate of σ^2. In this case then, M_g can be estimated by

(B17a) $$\hat{M}_g = \hat{B}_g + V_g ,$$

where

(B17b) $$\hat{B}_g = \frac{\mathbf{y}'\mathbf{R}_g\mathbf{y}}{\hat{\sigma}_f} - \mathrm{tr}(\mathbf{I}-\mathbf{S}_g)'(\mathbf{I}-\mathbf{S}_g) \ ,$$

(B17c) $$V_g = \mathrm{tr}\,\mathbf{S}_g{}'\mathbf{S}_g \ .$$

$\hat{B}_g$ is the contribution of bias to the estimated mean squared error, and V_g is the contribution of variance. Cleveland and Devlin show that $\hat{M}_g$ can be implemented as

(B18) $$\hat{M}_g = v_1 \frac{(\mathbf{y}'\mathbf{R}_g\mathbf{y} - \mathbf{y}'\mathbf{R}_f\mathbf{y})/v_1}{(\mathbf{y}'\mathbf{R}_f\mathbf{y})/\delta_1} + \delta_1 - n + 2\,\mathrm{tr}\,\mathbf{S}_g$$

$$= v_1\hat{F} + \delta_1 - n + 2\,\mathrm{tr}\,\mathbf{S}_f \ ,$$

where $\mathbf{y}'\mathbf{R}_f\mathbf{y}$ is the residual sum of squares when the smoothing parameter is f. Because there is an approximate *F*-distribution for $\hat{F}$—as mentioned above—a probability distribution for $\hat{M}_g$ can be derived. Cleveland and Devlin argue that the smoothing parameter f, for which the bias of the fitted values is negligible, is "usually in the range of .2 to .4"; we chose $f = 0.3$. Similar to the analysis of variance (B13), the *M*-plot method can easily be extended to linear models estimated with ordinary least squares.

Table 1

The table shows the results of an analysis of variance. The unrestricted model is the nonprametric regression equation $y_t = f(\mathbf{z}_t) + \varepsilon_t$. We estimate the model, using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988), for the time period May 20, 1991, through December 31, 2002. The dependent variable, y_t, denotes the daily excess return on Fannie Mae and Freddie Mac stock, respectively; the vector $\mathbf{z}_t$ comprises the observations of the explanatory variables at time t, and ε_t is an error term. The variables are detailed in Appendix A. The model is estimated for a smoothing parameter $g = 0.9$ (Fannie Mae) and $g = 0.95$ (Freddie Mac); these smoothing parameter values were found not to entail a statistically significant bias of the fitted values. We impose restrictions on the model by way of omitting variables or by means of imposing linearity on part of the model—resulting in the semi-parametric model $y_t = \beta \cdot x_t + f(\tilde{\mathbf{z}}_t) + \varepsilon_t$—or on the entire model—resulting in the linear model $y_t = \mathbf{z_t}'\boldsymbol{\beta} + \varepsilon_t$. We also impose an additivity constraint, which results in the generalized additive model $y_t = f_1(x_t) + f_2(\tilde{\mathbf{z}}_t) + \varepsilon_t$. In the semi-parametric and the generalized additive model, x_t is the time t market excess return and the vector $\tilde{\mathbf{z}}_t$ comprises all other explanatory variables included in $\mathbf{z}_t$. We estimate the semi-parametric model as suggested by Speckman (1988); for the generalized additive model, we use the backfitting algorithm developed of Hastie and Tibshirani (1986). The asterisk, *, denotes significance at the 1 percent level. DDF (NDF): Denominator (numerator) degrees of freedom. We calculate non-parametric confidence intervals from bootstrap percentiles for the difference in the variance between the unrestricted and the restricted model, using biased variance estimators (Hastie and Tibshirani, 1993). This bootstrapping technique rests on the sum of pair-wise differences of the squared residuals between the restricted and the unrestricted models without imposing the condition that each pair of observations is generated by the same zero-mean normal distribution.

Panel A: Fannie Mae			
	Analysis of Variance (DDF: 2,248)		90 Percent Non-parametric Bootstrap Percentiles
	NDF	F-Statistic	$\times 10^{-4}$
Market	70	16.265*	-0.990; -0.652
Short Rate	106	3.193*	-0.315; -0.134
Term Spread	115	4.095*	-0.329; -0.183
Short Rate and Term Spread (Joint Test)	135	5.648*	-0.401; -0.201
Nonconstant Explanatory Variables (Joint Test)	2,255	2.387*	-13,882; -13,846
Semi-parametric Model (Hypotheses 1 and 2)	117	45.657*	-1.107; -0.778
Generalized Additive Model (Hypothesis 2)	143	7.435*	-0.195; -0.072
Linear Model	159	3.383*	-0.214; -0.063

Panel B: Freddie Mac			
	Analysis of Variance (DDF: 2,248)		90 Percent Non-parametric Bootstrap Percentiles
	NDF	F-Statistic	$\times 10^{-4}$
Market	68	19.312*	-1.089; -0.707
Short Rate	101	3.236*	-0.270; -0.123
Term Spread	106	4.965*	-0.384; -0.019
Short Rate and Term Spread (Joint Test)	125	6.295*	-0.411; -0.182
Nonconstant Explanatory Variables (Joint Test)	2,250	3.888*	-24,689; -24,637
Semi-parametric Model (Hypotheses 1 and 2)	94	47.656*	-1.022; -0.686
Generalized Additive Model (Hypothesis 2)	122	10.078*	-0.230; -0.082
Linear Model	131	3.535*	-0.215; -0.046

Chart 1

The chart shows (along a 45° line) the return on a portfolio that consists of an equity claim and a long position in a down-and-in put option written on this claim. The strike price of this barrier option is set at the sum of the price of the underlying asset—the equity claim—and the option premium. (Starting from the price of the underlying asset, we use an iteration procedure to determine the strike price and the option premium.) The option is American-style with 92 calendar days to expiration and a barrier at $30; we adjust for daily monitoring using the algorithm suggested by Broadie, Glasserman, and Kou (1997). We set at 30 percent the volatility of the underlying asset, at 3 percent the continuously compounded risk-free rate (per annum), and at $1.80 the annual dividend payment (which is assumed to be compounded continuously). We assume 250 trading days per year. The returns are centered on an initial value of the equity claim of $38, which varies between $31 and $45 in incremental steps of $1.

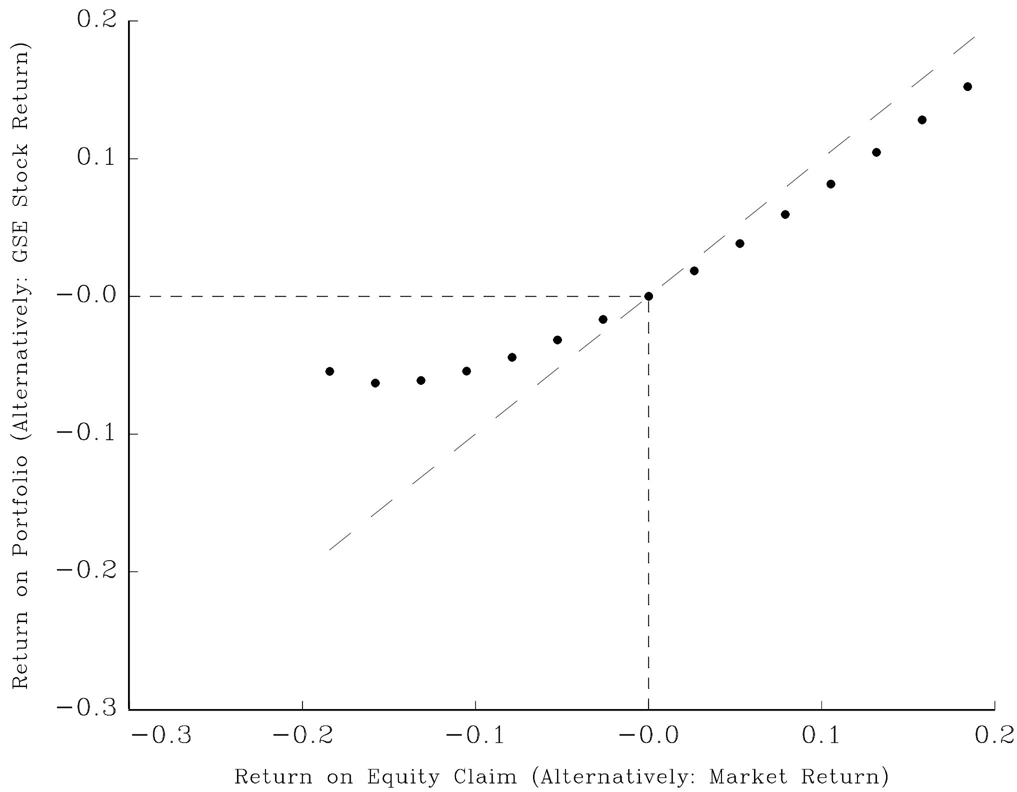

Chart 2

The chart shows (along a 45° line) the return on a portfolio that consists of an equity claim and a long position in a down-and-in put option written on this claim. The strike price of this barrier option is set at the sum of the price of the underlying asset—the equity claim—and the option premium. (Starting from the price of the underlying asset, we use an iteration procedure to determine the strike price and the option premium.) The option is American-style with 92 calendar days to expiration and a barrier at \$30; we adjust for daily monitoring using the algorithm suggested by Broadie, Glasserman, and Kou (1997). We set at 30 percent the volatility of the underlying asset, at 3 percent the continuously compounded risk-free rate (per annum), and at \$1.80 the annual dividend payment (which is assumed to be compounded continuously). We assume 250 trading days per year. The returns are centered on an initial value of the equity claim of \$38, which varies between \$27 and \$44 in incremental steps of \$1. For positive returns on the equity claim, the government raises the barrier such that the fraction of the option premium in the stock (that is, portfolio) price remains unchanged. For the (comparatively) small decline in the value of the equity claim from \$38 to \$37, the government lowers the barrier by \$2. For any decline in the present value of the dividend stream of \$2 or more, the government lowers the barrier by \$4.

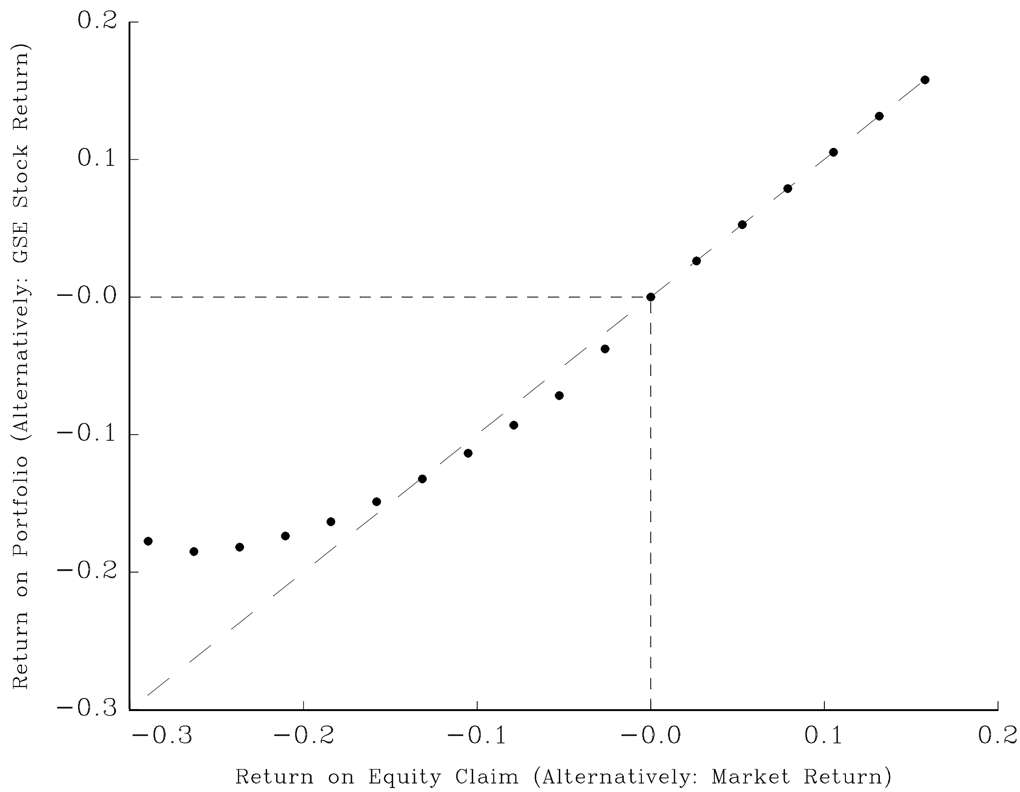

Chart 3

The chart shows a kernel estimate (thick line) of the probability density of daily excess return on Fannie Mae stock for the period May 20, 1991, through December 31, 2002. The excess return is defined as the difference between the log return on the stock and the log return on the risk-free asset. The return on the risk-free asset is measured by the return on an investment in the overnight eurodollar market. We use a Gaussian kernel along with an (under the null of normal distribution) optimal bandwidth of $(4/3)^{0.2} \cdot \hat{\sigma} \cdot T^{-0.2}$, where T is the number of sample observations and $\hat{\sigma}$ is the sample standard deviation (Silverman, 1986). The normal probability density (thin line) is the normal based on estimates of the sample mean and standard deviation. The whiskers indicate the dispersion of the observations on the horizontal axis. The skewness (0.125) and kurtosis (4.486) estimates are both statistically significant.

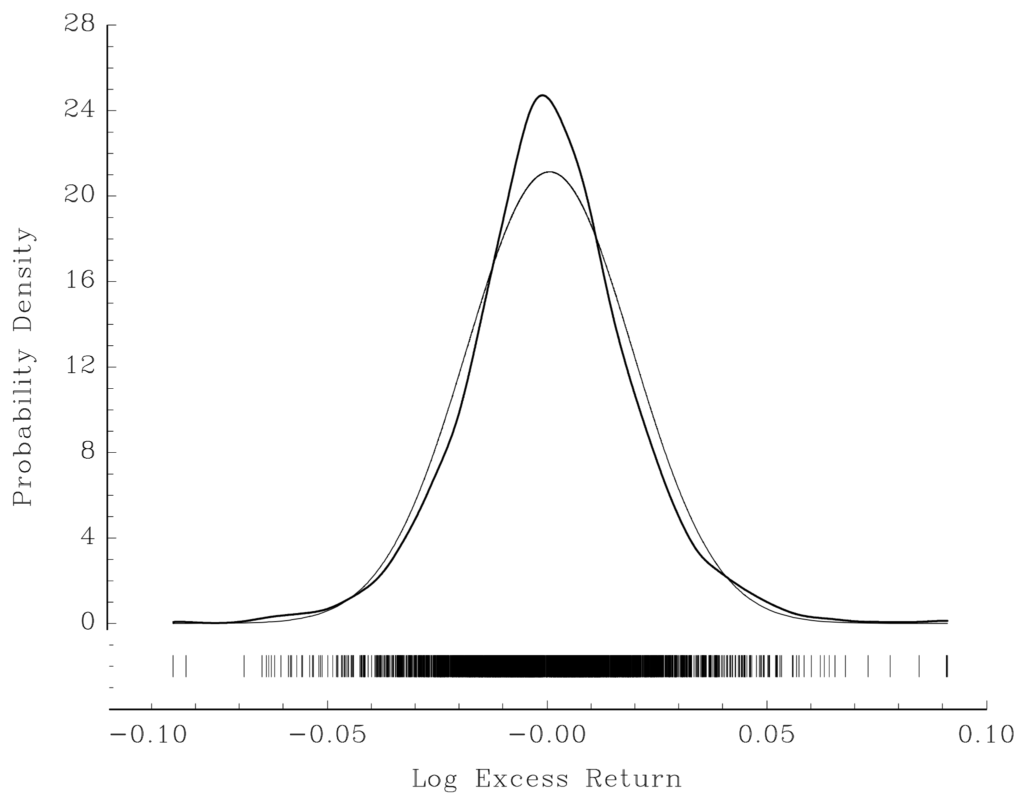

Chart 4

The chart shows a kernel estimate (thick line) of the probability density of daily excess return on Freddie Mac stock for the period May 20, 1991, through December 31, 2002. The excess return is defined as the difference between the log return on the stock and the log return on the risk-free asset. The return on the risk-free asset is measured by the return on an investment in the overnight eurodollar market. We use a Gaussian kernel along with an (under the null of normal distribution) optimal bandwidth of $(4/3)^{0.2} \cdot \hat{\sigma} \cdot T^{-0.2}$, where T is the number of sample observations and $\hat{\sigma}$ is the sample standard deviation (Silverman, 1986). The normal probability density (thin line) is the normal based on estimates of the sample mean and standard deviation. The whiskers indicate the dispersion of the observations on the horizontal axis. The skewness (0.261) and kurtosis (4.789) estimates are both statistically significant.

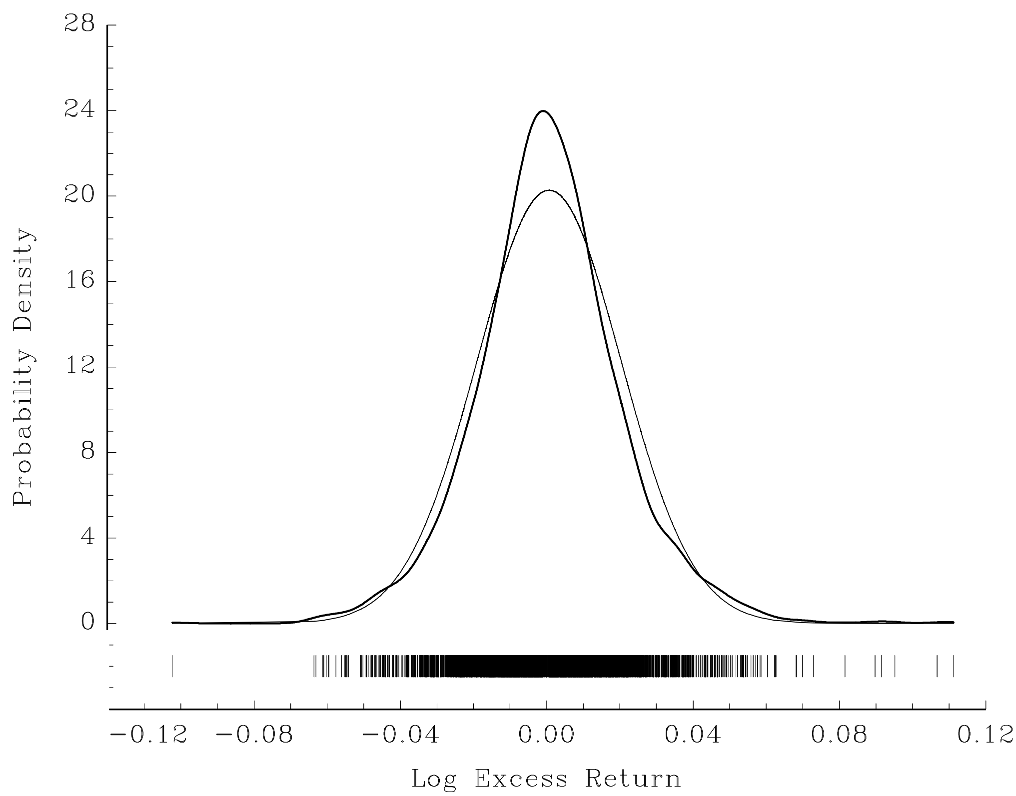

Chart 5

The chart shows an *M*-plot for Fannie Mae. We estimate the non-parametric model $y_t = f(\mathbf{z}_t) + \varepsilon_t$ using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988). The model is estimated for the period May 20, 1991, through December 31, 2002. The dependent variable, y_t, denotes the daily excess return on Fannie Mae stock; the vector $\mathbf{z}_t$ comprises the observations of the explanatory variables at time t, and ε_t is an error term. The variables are detailed in Appendix A. The *M*-plot shows the trade-off between the contributions of variance and bias to the mean squared error of the fitted values as the smoothing parameter, g, changes. The *M*-statistic is defined as $\hat{M}_g = V_g + \hat{B}_g$, where $\hat{B}_g$ is the contribution of bias to the estimated mean squared error, and V_g is the contribution of variance. V_g is shown as the equivalent number of parameters—a measure of the amount of smoothing done by the estimation procedure. On the diagonal line, $\hat{M}_g$ equals V_g. The smoothing parameter ranges from 0.3 (rightmost ×-symbol) to 1 (leftmost ×-symbol) in steps of 0.05. The □-symbol represents the *M*-statistic for the ordinary least squares fitting of the linearized model, $y_t = \mathbf{z_t}'\boldsymbol{\beta} + \varepsilon_t$. For details on the *M*-plot method see Appendix B.

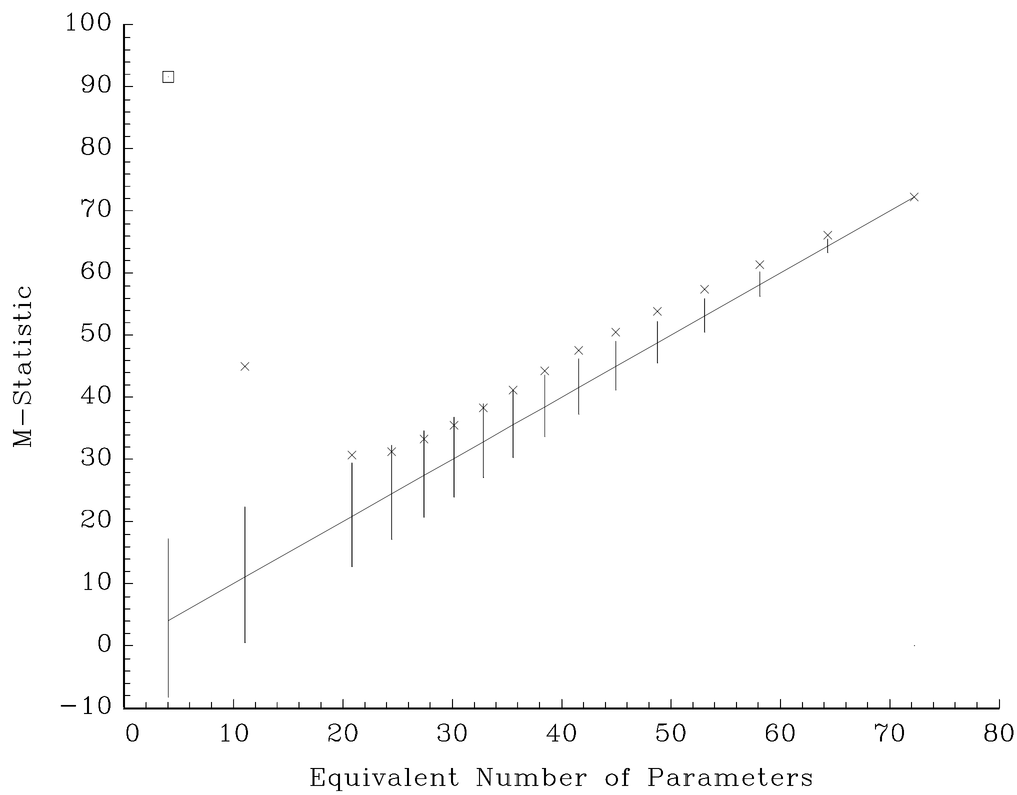

Chart 6

The chart shows an *M*-plot for Freddie Mac. We estimate the non-parametric model $y_t = f(\mathbf{z}_t) + \varepsilon_t$ using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988). The model is estimated for the period May 20, 1991, through December 31, 2002. The dependent variable, y_t, denotes the daily excess return on Freddie Mac stock; the vector $\mathbf{z}_t$ comprises the observations of the explanatory variables at time t, and ε_t is an error term. The variables are detailed in Appendix A. The *M*-plot shows the trade-off between the contributions of variance and bias to the mean squared error of the fitted values as the smoothing parameter, g, changes. The *M*-statistic is defined as $\hat{M}_g = V_g + \hat{B}_g$, where $\hat{B}_g$ is the contribution of bias to the estimated mean squared error, and V_g is the contribution of variance. V_g is shown as the equivalent number of parameters—a measure of the amount of smoothing done by the estimation procedure. On the diagonal line, $\hat{M}_g$ equals V_g. The smoothing parameter ranges from 0.3 (rightmost ×-symbol) to 1 (leftmost ×-symbol) in steps of 0.05. The □-symbol represents the *M*-statistic for the ordinary least squares fitting of the linearized model, $y_t = \mathbf{z_t}'\boldsymbol{\beta} + \varepsilon_t$. For details on the *M*-plot method see Appendix B.

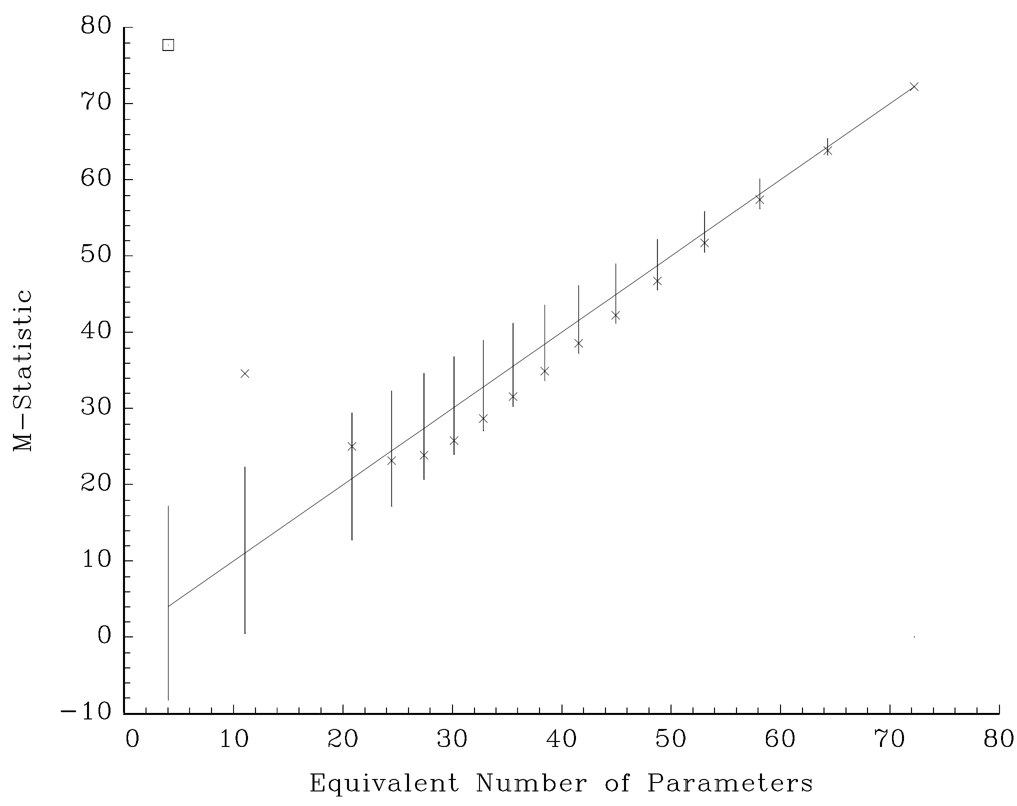

Chart 7

The chart shows sets of conditioning plots of the non-parametric model $y_t = f(\mathbf{z}_t) + \varepsilon_t$, applied to Fannie Mae stock during the period May 20, 1991, through December 31, 2002. The dependent variable, y_t, denotes the daily excess return on Fannie Mae stock; the vector $\mathbf{z}_t$ comprises the observations of the explanatory variables at time t, and ε_t is an error term. The excess return is defined as the difference between the log return on the stock and the log return on the risk-free asset. The return on the risk-free asset is measured by the return on an investment in the overnight eurodollar market. The explanatory variables comprise a vector of ones, the market excess return, the difference between the constant-maturity 3-month Treasury bill yield at times t and t-1, and the difference between the time t and time t-1 term spreads. The market excess return equals the difference between the log return on the CRSP value-weighted stock market index and the log return on the risk-free asset. The term spread is defined as the difference between the constant-maturity yields of the 10-year Treasury note and the constant-maturity 3-month Treasury bill. Note that the Treasury yields are recorded in percent. We estimate the model using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988). LOESS estimates the functional form in each observation based on a neighborhood that comprises the fraction g of the data points in the population. The data points in the neighborhood are chosen and weighted based on their respective Euclidean distance to the observation in question. We use a tri-cube weight function with locally quadratic fitting, as suggested by Cleveland and Devlin. The smoothing parameter, g, is set at 0.9. For each of the three explanatory variables, the regression results are presented in a set of 9 conditioning plots, as introduced by Cleveland and Devlin. Conditioning plots display the estimated partial impact of a chosen explanatory variable, with all other explanatory variables pegged to chosen constants. Because the intercept is not identified in this type of regression, only *changes* in the displayed partial impact (rather than the level itself) can be interpreted in an economically meaningful manner. The variable that is varied in a conditioning plot—shown on the horizontal axis—adopts only values that are actually observed in the neighborhood of the values at which the pegged explanatory variables are set. Specifically, when we peg a variable to its median negative (positive) value, only observations for which this variable adopts nonpositive (nonnegative) values are included in the conditioning plot. Similarly, when we peg a variable to zero, only observations for which this variable lies within the closed interval of the median negative value and the median positive value are included in the conditioning plot. From the thus chosen set of observations, we discard the ten most extreme observations (on either side) of the variable varied in the conditioning plot before evaluating the estimated functional form for the displayed range of values. The dashed lines denote 90 percent point-wise confidence bounds. The whiskers indicate the dispersion of the observations on the horizontal axis. For Panels B and C, the whiskers take on the shape of a frequency distribution because changes in the short rate and the yield spread are discrete.

Chart 7, *cont.*

Panel A: Market Sensitivity of Fannie Mae Stock

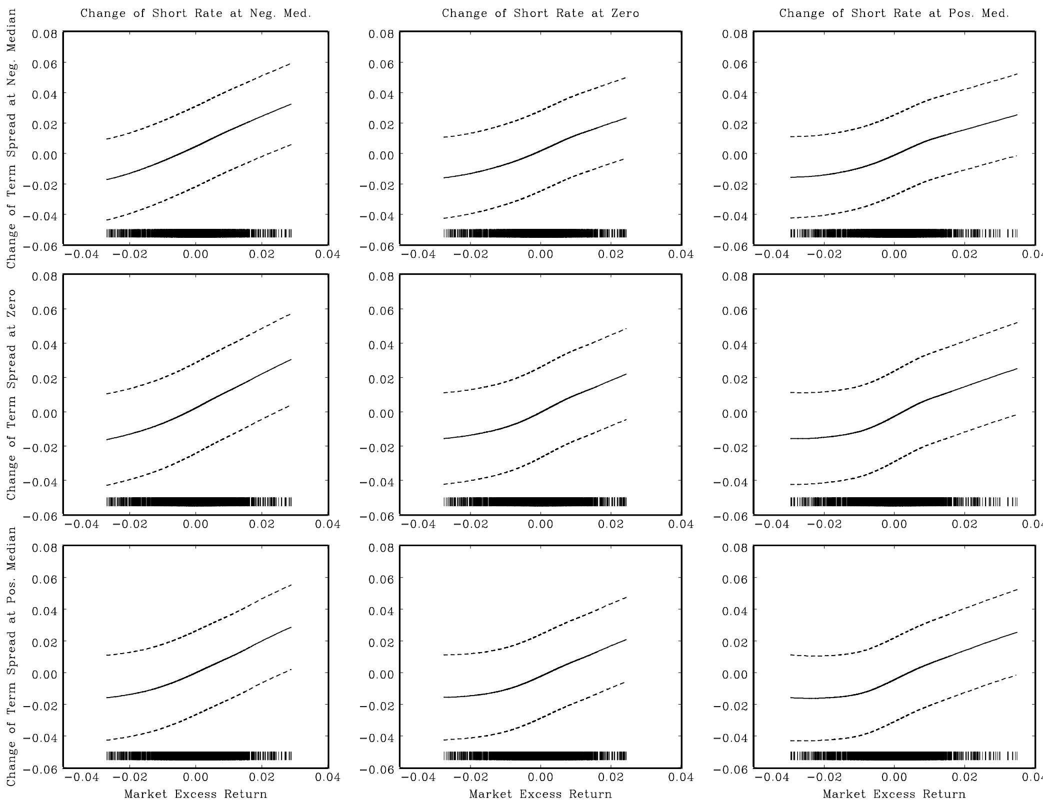

Chart 7, *cont.*

Panel B: Sensitivity of Fannie Mae Stock to the Short Rate

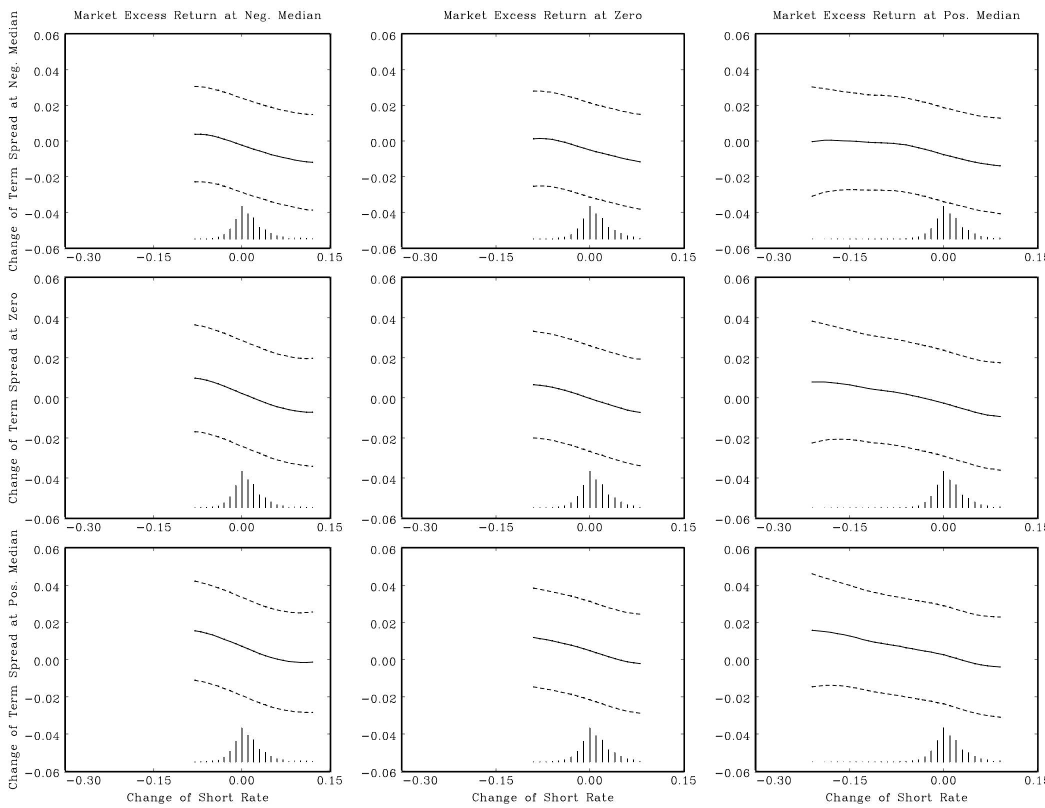

Chart 7, *cont.*

Panel C: Sensitivity of Fannie Mae Stock to the Term Spread

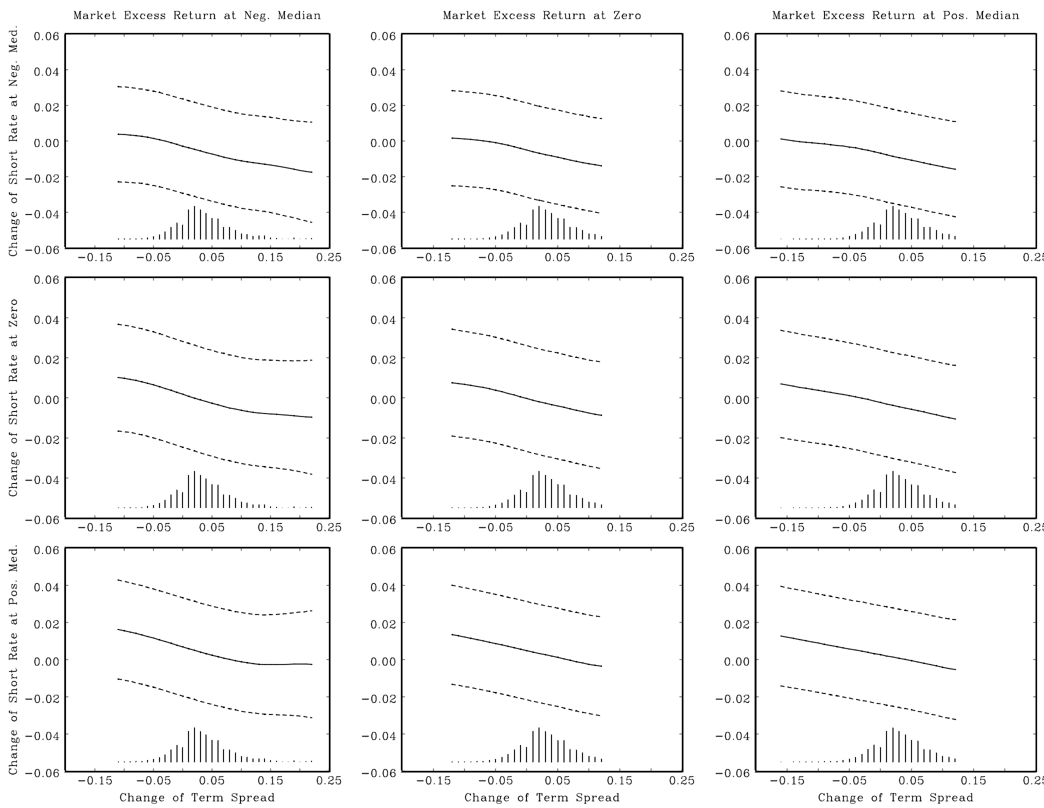

Chart 8

The chart shows sets of conditioning plots of the non-parametric model $y_t = f(\mathbf{z}_t) + \varepsilon_t$, applied to Freddie Mac stock during the period May 20, 1991, through December 31, 2002. The dependent variable, y_t, denotes the daily excess return on Freddie Mac stock; the vector $\mathbf{z}_t$ comprises the observations of the explanatory variables at time t, and ε_t is an error term. The excess return is defined as the difference between the log return on the stock and the log return on the risk-free asset. The return on the risk-free asset is measured by the return on an investment in the overnight eurodollar market. The explanatory variables comprise a vector of ones, the market excess return, the difference between the constant-maturity 3-month Treasury bill yield at times t and t-1, and the difference between the time t and time t-1 term spreads. The market excess return equals the difference between the log return on the CRSP value-weighted stock market index and the log return on the risk-free asset. The term spread is defined as the difference between the constant-maturity yields of the 10-year Treasury note and the constant-maturity 3-month Treasury bill. Note that the Treasury yields are recorded in percent. We estimate the model using the multivariate smoother LOESS (locally weighted regression) as developed by Cleveland and Devlin (1988). LOESS estimates the functional form in each observation based on a neighborhood that comprises the fraction g of the data points in the population. The data points in the neighborhood are chosen and weighted based on their respective Euclidean distance to the observation in question. We use a tri-cube weight function with locally quadratic fitting, as suggested by Cleveland and Devlin. The smoothing parameter, g, is set at 0.95. For each of the three explanatory variables, the regression results are presented in a set of 9 conditioning plots, as introduced by Cleveland and Devlin. Conditioning plots display the estimated partial impact of a chosen explanatory variable, with all other explanatory variables pegged to chosen constants. Because the intercept is not identified in this type of regression, only *changes* in the displayed partial impact (rather than the level itself) can be interpreted in an economically meaningful manner. The variable that is varied in a conditioning plot—shown on the horizontal axis—adopts only values that are actually observed in the neighborhood of the values at which the pegged explanatory variables are set. Specifically, when we peg a variable to its median negative (positive) value, only observations for which this variable adopts nonpositive (nonnegative) values are included in the conditioning plot. Similarly, when we peg a variable to zero, only observations for which this variable lies within the closed interval of the median negative value and the median positive value are included in the conditioning plot. From the thus chosen set of observations, we discard the ten most extreme observations (on either side) of the variable varied in the conditioning plot before evaluating the estimated functional form for the displayed range of values. The dashed lines denote 90 percent point-wise confidence bounds. The whiskers indicate the dispersion of the observations on the horizontal axis. For Panels B and C, the whiskers take on the shape of a frequency distribution because changes in the short rate and the yield spread are discrete.

Chart 8, *cont.*

Panel A: Market Sensitivity of Freddie Mac Stock

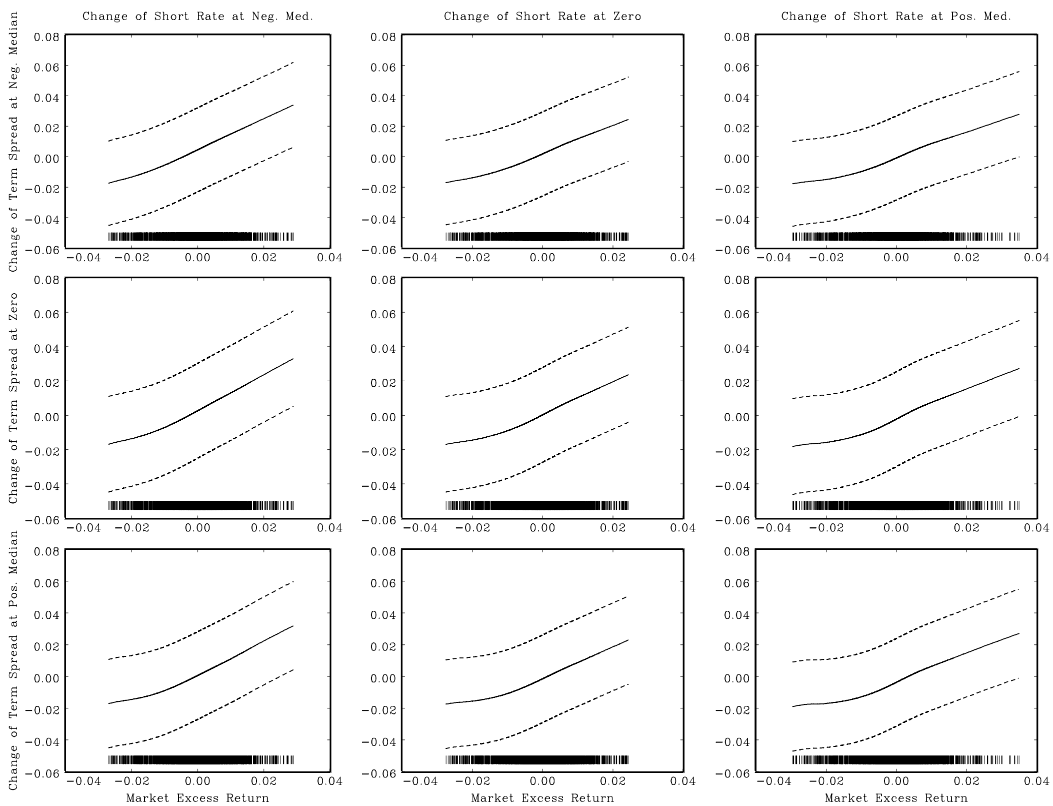

Chart 8, *cont.*

Panel B: Sensitivity of Freddie Mac Stock to the Short Rate

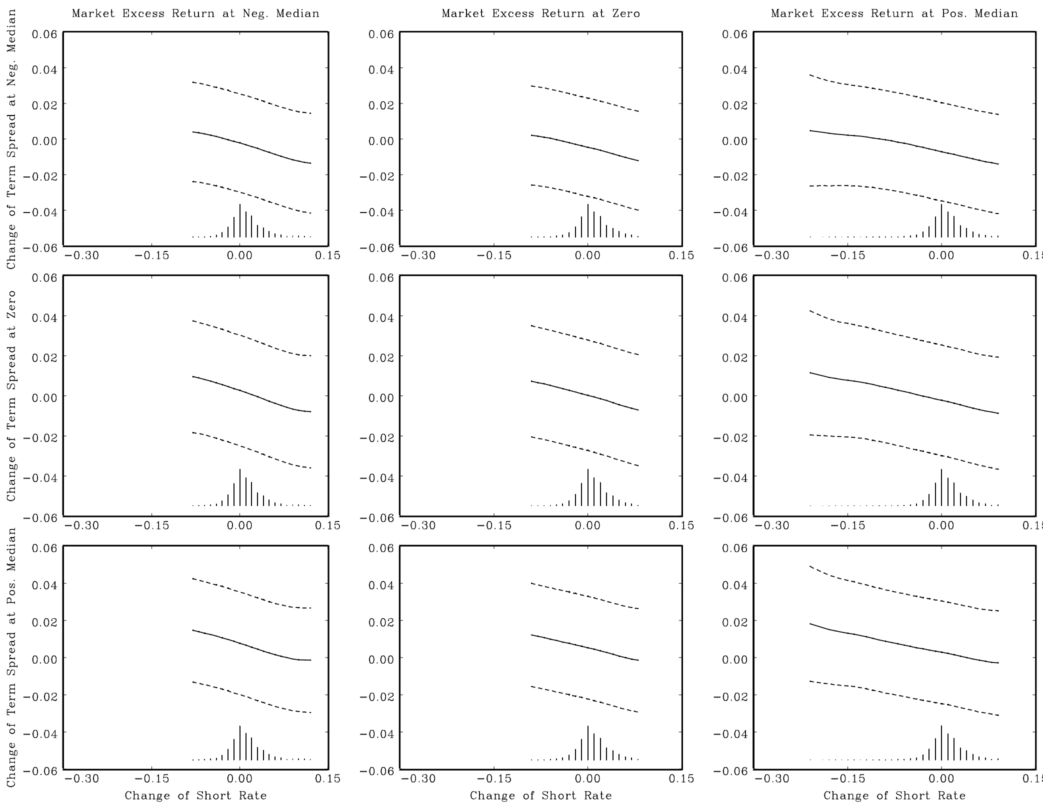

Chart 8, *cont.*

Panel C: Sensitivity of Freddie Mac Stock to the Term Spread