The Prime Rate Macroeconomy - a Stochastic Nexus

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ABSTRACT

How do macroeconomic conditions and financial markets form the prime rate process? I formulate economic and financial incentives as dynamics within the prime rate market that specify the macroeconomic transmission mechanism. Recognizing this transmission structure has significant implications for interest rate levels of private business loans. To identify the transmission mechanism, I posit a five-factor stochastic process. Each underlying factor corresponds to a distinct incentive and captures unique mean-reversion or time-delay characteristics. The main empirical finding is that formal recognition of the prime rate's transmission mechanism substantially reduces out-of-sample prediction error relative to standard interest rate stochastic processes.

Keywords: prime rate; transmission mechanism; market integration; inflation; Treasury bill; federal funds rate; stochastic differential equations

EconLit codes: C32; E43; E44; E47

1. Introduction

A central question for borrowers with loans or credit linked to the prime rate is: how do macroeconomic conditions and policy announcements affect the prime rate? This question puzzles many managers in private companies and individual borrowers assessing financial risk (Boivin and Giannoni 2006; Bassett et al. 2014; Fisher, Martineau, and Sheng 2022; Hann et al. 2025). Understanding the macroeconomic transmission mechanism that underlies the prime rate market will help borrowers determine the timing to initiate or repay a loan. Ultimately, answering their pressing question: should it be today or a year from now? Recognizing this longer-term mechanism is also critical for policymakers, who want to understand the possible paths and implications that their policy implementations may cause (Bundick and Smith 2020; Flodén et al. 2021; Gomez et al. 2021).

The prime rate is one of the main credit rates that determine the cost of loans in private markets. The prime rate is the market average interest rate that major banks offer to the companies with the least credit risk (Kosowski and Neftci 2015; Tobin 2018; Calomiris, Longhofer, and Jaffee 2018). Likewise, many bank loans to private businesses – where the repayment interest rate is commonly determined by a function of the prime rate – are also offered to individuals (Mishkin 2019; The Federal Reserve 2013). Similarly, the prime rate affects many privately held corporations and individuals, as it is the basis for their cost of borrowing (Federal Reserve 2025a; Tobin 2018). In fact, the final lending rate is determined by the risk characteristics of borrowers (Ben-David, Johnson, and Stulz 2025; Liberti and Petersen 2019).

The prime rate is affected by monetary policy and the general state of interest rates that affect borrowers' choices (Gertler and Karadi 2015; Bretscher, Schmid, and Vedolin 2018; Lindsey and Wallich 2018; Pascal 2020; Moder 2023). Through this transmission mechanism, these bank loans are affected by the federal funds rate (funds rate), since this is a funding cost for the bank (Kobayashi 2009; Wang 2013; Miranda-Agrippino and Ricco 2021). Circa 1994, the prime rate is approximately three percent above the federal funds rate (Garriga-Montoriol and Wang 2011) and is shown in Figure 2. In turn, the Federal Reserve uses interest rates as a transmission method through which to impact economic activity at large. Noting the magnitude of private loans in the economy, (Federal Reserve 2025b) reported that at the end of 2024, the market size of commercial loans alone was approximately 2.79 trillion USD. Therefore, understanding the causal macroeconomic transmission mechanism has essential implications as it determines the cost of lending, the discount rate (i.e., required rate of return), or commercial projects' valuations (Gormsen and Huber 2025).

Similar to (Christensen and Rudebusch 2019), who use a finance-based method of stochastic differential equations to obtain an equilibrium macroeconomic estimate of the real interest rate, I propose a monetary-transmission mechanism. In this study, I contribute a theoretical five-factor stochastic differential equation that describes the integration of financial markets and macroeconomic conditions within the prime rate market. The benefit of a stochastic process, rather than a regression analysis, is its usefulness for the construction of systems, markets, or transmission mechanisms, because it permits a theoretical study that provides further insights into their interactions. Additionally, a

stochastic process allows for the preservation and combination of unique dynamics of each market's process characteristics on its own terms. Likewise, the transmission mechanism can be stated as closely as possible to reality while integrating its inherent randomness and fluctuations. My empirical contribution is to simulate this stochastic macroeconomic transmission mechanism on an annual basis for the US prime rate.

On the one hand, looking at the formulation of general term-structure stochastic differential equations (SDE) (e.g. Vasicek, CIR, or Heston), they often fail to account for the economic incentive structure that drives an interest rate. On the other hand, the prime rate is not a risk-free rate but an average benchmark for commercial lending. To fill this gap, I model the macroeconomic transmission mechanism explicitly by incorporating factors representing banks' funding costs, investment alternatives, and risk compensation. Therefore, I formulate the determining factors of the prime rate as a depiction of the economic incentive structure for the commercial banking sector. Although rate setters do not necessarily discuss these considerations, the factors reveal the prime rate market dynamics. This process characterizes the causal and correlative economic elements that structure the prime rate market. It follows that this stochastic process demonstrates the theoretical transmission mechanism by which financial and macroeconomic conditions determine the prime rate equilibrium.

The article proceeds as follows. Section 2 describes the formulation of the prime rate macroeconomy transmission process. Section 3 presents the estimation procedure and alternative benchmark processes in detail. Section 4 provides the quantitative analysis, and Section 5 concludes.

2. The prime rate process

2.1 Transmission mechanism

In this section, I formulate the transmission mechanism as a function of the integration of markets underlying the prime rate market. This integration occurs since the prime rate is affected by financial markets and macroeconomic conditions. In aggregate, this represents the commercial banking sector decision-making and pricing challenge. Consequently, it passes through to private corporations and households.

Therefore, I define the prime rate process as a function of economic incentives and risks that form distinct underlying factors which determine the prime rate. Note that the underlying assumption of the process is that the commercial banking sector aims for profit maximization. Hence, the factors represent different markets (incentives or risks) increments that refer to the prime rate, as shown in equation (1). The two underlying factors of the drift represent the profit incentive. These bank-operational factors are the investment equation (8) and funding equation (8). The third and fourth underlying factors of the diffusion term represent risk incentives. These are general market uncertainties, volatility equation (11), and inflation equation (10). These factors represent risks the bank must manage. Consequently, the diffusion term is driven by risks that erode the real profit margin.

It follows that it is necessary for the prime rate to maintain a positive increment to offset its risks and incentives. Therefore, for the investment (identified by the Treasury bill) factor, a greater rate of return is required to compensate for the higher risk; for the funding (identified

by the federal funds rate) factor, a profit is required; the increment of the prime rate over inflation shows that the value of money is maintained.

Furthermore, the operational factors are assumed to be governed by the growth expectation μ of the prime rate (1), because the commercial banking sector does not have an incentive to decrease the rate; rather, this sector possesses an incentive to increase the rate, which increases its profitability. In addition, two competing assumptions regulate the integrated markets within the drift of the prime process: the second assumption is mean-reversion α equation (3), and the third assumption is the value-of-information $\overline{\rho}$ equation (4).

First, I formulate the prime rate process as a function of the market's incentive structure, regulated by the growth rate, as follows:

$$dP = \mu\big([P - r_i] - \big[P - r_f\big]\big)dt + \sigma(P - \pi)dW, \qquad (1)$$

where P is the prime rate, μ is the prime rate growth rate, r_i is the return on investment identified by the 3-month Treasury bill: secondary market rate (T-Bill), r_f is the rate of funding identified by the effective federal funds rate, σ is the prime rate volatility, π is inflation measured by the Consumer Price Index (CPI), and dW is the Wiener process.

Furthermore, assume that the markets are fully integrated. Thus, the process is not defined by the increments to the prime rate $[P - r_i]$ and $\big[P - r_f\big]$. Hence, combining the increments to the prime rate $(P - r_i)$ and $\big(P - r_f\big)$, obtains the solution to the market integration $\big(r_f - r_i\big)$. Consequently, the prime rate process is defined as follows (GPRIME):

$$dP = \mu\big(r_f - r_i\big)dt + \sigma(P - \pi)dW. \qquad (2)$$

Furthermore, suppose that mean-reversion regulates the integrated markets; then the process is defined as follows (RPRIME):

$$dP = \alpha\left(r_f - r_i\right)dt + \sigma(P - \pi)dW, \qquad (3)$$

where α is the prime rate's mean-reversion.

Moreover, I propose a third assumption that regulates the integration of markets: the value-of-information metric; (Kyle 1985; Back, Cao, and Willard 2000; Collin-Dufresne and Fos 2016; Kadan and Manela 2025). Following the interpretation presented by (Kadan and Manela 2025), the value-of-information is measured by a "ratio of fundamental variance to price impact". This ratio signals that a reduction in uncertainty and price impact are both supportive of a higher information value. Thus, I suggest a value-of-information metric $\overline{\rho}$ applicable to private markets, $\overline{\rho} = \rho\frac{\overline{\sigma^2}}{\overline{p}}$ where $\overline{\sigma^2}$ is the average variance, $\overline{p}$ is the average of the prime rate, ρ is the correlation between the variance and the prime rate's average. This straightforward metric underlines the fundamental relationship within the value-of-information in a private market. This highlights the tradeoff in private markets between price and its dispersion. Greater fundamental volatility with a higher correlation between the dispersion and the underlying asset price, increases the value of private information, whereas a higher price diminishes it.

Hence, the information value prime rate process (IVPRIME) is defined as follows:

$$dP = \overline{\rho}\left(r_f - r_i\right)dt + \sigma(P - \pi)dW, \qquad (4)$$

where $\overline{\rho}$ is the information value metric.

A consequence of the multitude of predictions is that one miscalculated estimate by the prime rate setter of the funding, investing or inflation factors can generate a loss for the bank. Consequently, banks should calibrate and monitor these factors; however, this does not mean that this is how a single lending institution operates. Thus, as demonstrated, the

process portrays the formation in aggregate within the prime rate market as a transmission mechanism of integration of markets.

2.2. Operational Factors

One of the key funding options for banks is loans from the Federal Reserve, which are set by the funds rate. A multitude of studies provide evidence that the Federal Reserve uses the funds rate to impact prevailing interest rates; (De Bondt 2005; Payne and Waters 2008; Kashyap and Stein 2012; Apergis and Cooray 2015; Andries and Billon 2016; Horvath 2017; Lenel, Piazzesi, and Schneider 2019; Akcay and Elyasiani 2021).

In addition to loan origination, one type of investment opportunity for a bank is Treasury bills; (Dueker 2000) documented the existence of a correlation between Treasury bills and the prime rate (also see Table 1). Under this economic regime, the economic incentive of the prime rate setter is to maintain a positive increment from the operational alternatives, with an aim of profit maximization. The investment factor – the prime rate to T-Bill increment, and the funding factor – the prime rate to the funds rate increment, are presented in Figures 1 and 2. Note that the funding expenses were miscalculated, as occurred in 1969 and 1973 (Figure 2), where a positive increment was not maintained.

[Figure 1 here]

[Figure 2 here]

I begin by formulating the base process for both operational factors. The drift term is the forward expectation over the current rate, governed by mean-reversion. The diffusion term is the systematic risk proportional change. Thus, the stochastic process framework for the operational factors is defined accordingly:

$$dS = \alpha(F - b)dt + \sigma S dW \quad (5)$$

where *S* is the current rate, *F* is the forward expectation of the asset, *α* is the instantaneous mean-reversion rate (IMR), *b* is the current mean, *σ* is the volatility and *dW* is a Wiener process.

This process diverges from the standard formulation of a drift term of a mean-reversion process. In comparison, (Sundaresan 2000) presented the conventional formulation of a mean-reversion process, as in (Vasicek 1977; Cox, Ingersoll, and Ross 1985; Courtadon 1982; Chan et al. 1992; Duffie and Rui 1996; Brennan and Schwartz 1979; Heston 1993); the drift term takes the form of $\alpha(b - s)dt$. The first invocation of this physical process (originally described as the "behavior of a particle" by (Uhlenbeck and Ornstein 1930) as an adaptation of the interest rate process emanated from the probability distribution characteristics and convergence properties of the process; see (Vasicek 1977). This process was adapted to macroeconomic states of long-run equilibrium in interest rates (Christensen and Rudebusch 2019). The economic distinction between the conventional formulation and the drift term in equation (5) rests upon the outlook emphasis that dictates price behavior. The conventional formulation asserts that the spot rate margin is under the current mean. In contrast, equation (5) states that forward-looking information is priced into asset prices and is relative to the current state of asset prices.

Moreover, both operational factors trade continuously and are integral to capital markets. Therefore, assume both processes have a forward-looking characteristic. Considering the forward-looking characteristic, the classic forward formula F (6) is chosen to represent this assumption. Let

$$F = Se^{i(T-t)}, \tag{6}$$

where S is the spot rate, i the risk-free rate, T is time, and F is the forward rate. Combine equation (6) with process (5), and apply Itô's (1951) lemma, defined as follows:

$$dF = \left(\frac{dF}{dS}a(s,t) + \frac{dF}{dt} + \frac{1}{2}\frac{d^2F}{dS^2}b(s,t)^2\right)dt + \frac{dF}{dS}b(s,t)dW. \tag{7}$$

Then the solution to the mean-reverting forward-looking process is as follows:

$$dF = [A(F-b) - rF]dt + \sigma F dW, \tag{8}$$

$$where\ A = \alpha e^{i(T-t)}. \tag{9}$$

A is then defined as the trend instantaneous mean-reversion (TIMR). In this formulation, *A* is the interaction of instantaneous mean-reversion with a risk-free growth rate. This form elucidates the interpretation of this seemingly complex process. The initial growth rate expectation *F* increases over the current mean b, during which the TIMR regulates its position. To avoid overestimation, the process is corrected by subtracting the risk-free rate from the forward-rate interaction. The uncertainty of the process is the interaction of volatility and forward-state expectation. Both the T-Bill and the federal funds rate are liquid, readily accessible assets for the banking sector and are traded continuously in capital markets. In view of these similarities, there is a built-in equivalency assumption in the behavior of both processes.

2.3 Risk Factors

In real terms, banks incur a loss when inflation rises above the prime rate. In *1974, 1975, 2021* and *2022*, the prime market was in this economic state (in *2011*, the difference was only 0.0009) (Figure 3). This demonstrates that inflation is nonconstant and volatile and that banks are not always capable of maintaining a positive increment of the prime rate over the

inflation rate. Hence, I further incorporate this real risk as a distinct factor. Note that the inflation expectation, unlike the operational factors, does not possess the formal forward-looking characteristic of a stochastic process. In fact, inflation represents current prices and does not incorporate discounted future information. Therefore, the expectation of the inflation factor drift is the interaction of the instantaneous mean-reversion rate with the increment of current inflation relative to its mean. The diffusion term is the interaction of the inflation rate and its volatility, as follows:

$$d\pi = \alpha(\pi - b)dt + \sigma_\pi \pi dW \qquad (10)$$

where π is the inflation rate, α is the *IMR*, b is the current mean, and σ_π is the inflation volatility.

[Figure 3 here]

Similarly, to inflation, the volatility of the prime rate is assumed to be nonconstant and follows a distinct stochastic process. In addition to mean-reversion, volatility is not immediately realized and exhibits an inherent time delay. One of the first differential equations that models delay reactions with oscillations dates back to the (Mackey and Glass 1977) equation. Several studies have presented different results of delay reactions or oscillations within the context of financial stochastic processes. Examples include the stochastic generalization of the Mackey–Glass equation by (Nguyen 2012), the magnitude of the delay dependency in prices by (Luong and Dokuchaev 2016), and the application of independent and identically distributed (i.i.d.) processes in time-series analysis (Kyrtsou and Terraza 2003) and in the analysis of macroeconomic data (Kyrtsou and Vorlow 2009).

Furthermore, another distinguishing characteristic of this volatility is that the process produces periods of higher and lower levels of variation (Figure 4). Although volatility clustering exists in some time intervals, the more prevalent characteristic is rapid oscillation. In fact, given that the volatility time series is strictly finite and nonnegative, these properties contribute to forming a mean-reversion characteristic in the prime rate's volatility. Therefore, these two characteristics of mean-reversion and time delay are reconciled as an interaction in the drift of the delay process and are formulated as follows:

$$d\sigma = \alpha(\sigma_t - \kappa)dt + \alpha\sigma_t^2 dW \quad (11)$$

$$where\ \kappa = (\sigma_t - \sigma_{t-\tau})e^{-\sigma_t}. \quad (12)$$

where α is the IMR, σ_t^2 is the variance at time t, σ_t is the volatility at time t, and $\sigma_{t-\tau}$ is the volatility at time t-τ. Within the drift of the process, the increment of the delay is related to the delay's capacity κ. κ is the interaction of the volatility time increment $(\sigma_t - \sigma_{t-\tau})$ and a volatility's discount $e^{-\sigma_t}$. $(\sigma_t - \sigma_{t-\tau})$, states that market participants do not have an immediate reaction to the current price and that the reaction depends on the previous market rate. Hence, the current rate is dependent on its previous rate, which constitutes the magnitude of the delay. However, the interaction between mean-reversion and delay magnitude is not fully realized immediately, because market participants require additional time to integrate all available information into the current rate. Thus, their interaction has a discount effect at the current risk level of $e^{-\sigma_t}$. To compare with the diffusion, only the accuracy of the measurements of α and σ are considered.

[Figure 4 here]

3. Estimation

3.1 Monte Carlo simulation procedure

In this study, I conduct parsimonious simulations that emphasize the interpretability of Monte Carlo simulations. The discretization approach, (Kloeden and Platen 1992; Glasserman 2003; Brigo and Mercurio 2007), used for the processes is based on the Euler–Maruyama method:

$$\Delta r = a(r,t)\Delta t + b(r,t)\epsilon\sqrt{\Delta t}.$$

Where $a(r,t)$ is the integrand of the drift term and $b(r,t)$ is the integrand of the diffusion term of each process. In addition, ϵ is a sample drawn from a standard normal distribution. To maintain full interpretability of the simulations, stratified sampling with four decimal points is used, see (Boyle, Broadie, and Glasserman 1997; Kroese, Taimre, and Botev 2013; Brandimarte 2014; Hull 2022). $N^{-1}\left(\frac{i-0.5}{n}\right)$, where N^{-1} is the inverse cumulative normal distribution, *i* is an interval, and there are *n* intervals (one thousand). In addition, recall that stratified sampling for a Monte Carlo simulation has the benefit of reducing the variance in the simulation results.

(Hanson and Stein 2015; Nakamura and Steinsson 2018; Jarociński and Karadi 2020; Miranda-Agrippino and Ricco 2021; Bauer, Pflueger, and Sunderam 2024), find that monetary transmission causally affects the term structure of interest rates in the long-run. To isolate long-run monetary policy transmission without short term noise, the processes are simulated at annual intervals. The calibration proceeds with a single-interval predictions with a filtration adapted to the two preceding intervals. Consequently, the

annual simulation treats the transition density as the evolution of the macroeconomic conditions affecting the prime rate market.

3.2 Parameter Estimation

Within the debate on the pertinent risk-free rate, there are two main opinions. On the one hand, (Johannes and Sundaresan 2007) advocate for the London Interbank Offered Rate or its successor, the Secured Overnight Financing Rate (Klingler and Syrstad 2025); on the other hand, (Hull and White 2013) and Hull and White (2015) favor the funds rate. Among these rates, the funds rate is the only rate available for the entire time series. Therefore, the choice of a risk-free rate in this study is in accordance with Hull and White (2013), Hull and White (2015), Yin and Yang (2013), Maio (2014), Kakhkharov and Bianchi (2022), Curfman and Kandrac (2022). Therefore, the forward formula uses the funds rate i for compounding and is defined as follows:

$$\hat{F} = re^{i\Delta t}.$$

The volatility measure is the sample standard deviation:

$$\hat{\sigma_t} = \sqrt{\frac{\sum_{t=0}^{T}(r_t - \bar{r})^2}{T-1}},$$

and μ is the asset's expected growth rate:

$$\hat{\mu} = ln\,(\frac{r_T}{r_{T-t}}),$$

and the instantaneous mean-reversion rate is calculated according to the following metric:

$$\hat{\alpha} = \frac{ln\,(\frac{\bar{r}}{r_t})}{T},$$

(see Rabinovitz (2017)), where $\overline{r}$ is the arithmetic mean, r_t is the current rate, and T is the time interval. It is easily seen that IMR measures the continuous rate at which the price deviates from the mean for a fixed time interval. Note the limit of IMR, $\lim_{r_t \to \overline{r}} \left(\frac{ln\left(\frac{\overline{r}}{r_t}\right)}{T} \right)$: when r_t approaches $\overline{r}$, α is at parity. Moreover, given that r approaches zero (for example, in the volatility time series), α is undefined. Therefore, the function cannot be estimated, and α and its interactions are negated within the process. Furthermore, given that $\overline{r} < 0$ and $r_t > 0$ or $b > 0$ and $r_t < 0$, (for example, in the inflation time series), the ratio is negative, and the natural logarithm is only defined on R^+; thus, α cannot be computed. Consequently, to resolve the lack of computability due to a domain, a one-to-one transformation is applied, where the exponential transformation is implemented to those observations. Therefore, the transformation of the time series from a negative domain to a positive range permits α to be computed. Subsequently, an inverse transformation is applied to the results of the formula. For proof of the transformation and its applications see (Stewart 1991; Greene 2020).

3.3 Convergence Test

To demonstrate the validity and confirm the economic interpretability of a stochastic process in a time-series, a convergence rate test criterion (CR) is used. This method is a straightforward implementation of the acceptance-rejection method found in (Brandimarte 2014; Tsay and Chen 2019; Kawai and Imai 2012) for a time series and implemented in (Rabinovitz 2017). The method measures the percentage of predictions that converge over a time-series of predictions. Accordingly, convergence for a given numerical simulation is achieved when $f(P)_{n-1} \cap f(P)_n$ exists and is confirmed by measurement. To compute a

single series set, an indicator function $1_C(f(P))$, is successful when the simulation expectations converge to a constant:

$$1_C(f(P)) = \begin{cases} 1, & if\ f(P)_{n-1} \cap f(P)_n \\ 0, & if\ f(P)_{n-1} \cap f(P)_n = \emptyset. \end{cases} \quad (13)$$

Therefore, the minimum convergence rate criterion for an entire time series prediction is set at 95%, as follows:

$$\frac{1}{n}\sum_{i=1}^{n} 1_C(P)_i \geq 0.95. \quad (14)$$

Hence, if the numerical solutions of a stochastic differential equation fail to converge consistently over time, this presents statistical evidence that the stochastic process has not captured the underlying economic dynamics of the asset during the sample period. On the other hand, if the average indicator function exceeds the threshold over time, this presents statistical evidence that the stochastic process does capture the underlying economic dynamics of the asset during the sample period. Consequently, the lack of convergence of an SDE indicates a structural instability and excludes it from further consideration.

3.4 Prediction Accuracy Measurements

The goodness-of-fit measurements are the root mean square prediction error (RMSPE), and the relative root mean square prediction error (RRMSPE) in comparison to the GPRIME. In addition, t-tests and F-tests are used to compare whether a statistically significant difference exists between the prediction of each process and the prime rate. Hence the null hypothesis states: there is no statistically significant difference between the prediction and the prime rate observation. The alternative hypothesis states: there is a statistically significant difference, between the prediction and prime rate observation. Furthermore, the

time-series out-of-sample R^2 is defined as $R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \bar{r}_t)^2}$ that measure the prime rate predictability, as shown in (Campbell and Thompson 2008; Han et al. 2024; Hawinkel, Waegeman, and Maere 2024). Moreover, I present Q-Q plots comparing the predictions with the observed prime rate.

3.5 Encompassing Test

To further validate the results, the next step in this study evaluates the processes through an encompassing test initially proposed by (Diebold and Mariano 1995) and subsequently modified by (Harvey, Leybourne, and Newbold 1997) (HLN test). In the context of this paper, the encompassing test is utilized to validate whether the stochastic process that exhibits a smaller loss function (i.e., prediction error) is statistically significant when compared to a stochastic process that exhibits a higher loss function. The loss function used in this study is the mean square error (MSE):

$$g(e) = \frac{1}{n}\sum_{i=1}^{n} e_i^2. \tag{15}$$

Furthermore, the HLN test statistic is defined as follows:

$$HLN\ Test = \frac{\overline{(g(e_{1,t}) - g(e_{2,t}))g(e_{1,t})}}{\sqrt{\frac{\gamma_0 + 2\sum_{k=1}^{h-1}\gamma_k}{T}}} \sqrt{\frac{T + 1 - 2h + T^{-1}h(h-1)}{T}} \tag{16}$$

where $g(e_{1,t})$ and $g(e_{2,t})$ denote the loss functions of processes *1* and *2* at time *t*, respectively; γ_k is the autocovariance at lag *k*, *h* is the number of lags; and *T* is the number of intervals in a time series predictions.

It follows that the null hypothesis H_0 is that process 1 encompasses process *2*, and the rejection of H_0 suggests that the encompassing of process *2* by process *1* is inconclusive,

as defined in (Enders 2014; SAS Institute Inc. 2024; Masini, Medeiros, and Mendes 2023; Conlon, Cotter, and Eyiah-Donkor 2024; Gobato Souto and Moradi 2024). The test statistic is compared to critical values from a t-distribution table, adjusted for the degrees of freedom consistent with the number of prediction intervals in the time-series.

3.6 Benchmark Processes

Note that, in this sample, the prime rate is correlated with its volatility (see Table 1 for summary statistics). Therefore, the selected benchmarks are stochastic processes in which the interest rate is correlated with its volatility. Since this is the first stochastic process to model the prime rate, the following selected benchmark interest rate processes are chosen to represent different and distinctive characteristics.

The first stochastic differential equation benchmark is the (Heston 1993) process, which extends geometric Brownian motion, given that a financial asset and its volatility are correlated. Moreover, the volatility factor is mean-reverting, see (Cui, Li, and Zhang 2024; Yang, Ma, and Cui 2025; He, Wei, and Lin 2025; Feng et al. 2025). Consequently, the Heston process is formulated as follows:

$$dr = \mu r dt + \sqrt{\sigma^2} r dW \tag{17}$$

$$d\sigma^2 = \alpha\left(\overline{\sigma^2} - \sigma^2\right) dt + \sigma_V \sqrt{\sigma^2} dZ,$$

where r is the prime rate, μ is the growth rate, σ^2 is the variance, α is the mean-reversion rate, $\overline{\sigma^2}$ is the mean of the variance, σ_V is the volatility of the variance, and dW and dZ are Wiener processes.

Unlike the Heston SDE, which assumes mean-reversion in the volatility factor, the second benchmark assumes that mean-reversion exists within the asset itself. The most well-

known process is the one-factor SDE of (Vasicek 1977; Carr and Wu 2023; Goliński and Spencer 2023; Rebonato 2023), which was extended into a two-factor process by (Hull and White 1994) (HW2F). The HW2F is formulated as follows:

$$dr = (\mu - \alpha r)dt + \sigma_r dW \tag{18}$$
$$d\mu = -\overline{r}\mu dt + \sigma_\mu dZ,$$

where r is the prime rate, μ is the growth rate, α is the mean-reversion rate, σ_r is the volatility of the prime rate, $\overline{r}$ is the average prime rate, σ_μ is the volatility of the growth rate, and dW and dZ are Wiener processes.

The third interest rate process benchmark differs from the previous two processes and captures forward-looking characteristics. Hence, rather than modeling the prime rate's spot rate, the forward rate is modeled. A popular process that is forward-looking and is correlated with its volatility is the SABR model (Hagan et al. 2002; Cui, Li, and Zhang 2024; Michielon et al. 2024; Yang, Ma, and Cui 2025). Moreover, unlike the other processes, the SABR process does not possess a drift. Furthermore, it is focused on measuring the degree of uncertainty through the forward rate's volatility and its volatility of volatility. The SABR model is formulated as follows:

$$dF = \sigma_F F dW \tag{19}$$
$$d\sigma_F = \nu\sigma_F dZ.$$

where F is the forward rate, σ_F is volatility of the forward rate, ν is the volatility of volatility of the forward rate, and dW and dZ are Wiener processes.

The fourth benchmark, the two factor Cox-Ingersoll-Ross (CIR2) (Brigo and Mercurio 2007; Vrins and Wang 2023) process is formulated as follows for the prime rate application:

$$dr = \alpha_r(b_r - r)dt + \sigma_r\sqrt{r}dW$$

$$d\sigma_r = \alpha_{\sigma_r}\left(b_{\sigma_r} - \sigma_r\right)dt + \sigma_r\sqrt{\sigma_r}dZ,$$

where r is the prime rate, σ_r is the prime rate volatility, b_r and b_{σ_r} are the mean of r and σ_r respectively, α_r, α_{σ_r} are the mean-reversion rates of r and σ_r respectively, and dW and dZ are Wiener processes. In contrast to the other benchmarks, the distinctive characteristic of the CIR2 is that both factors are added for the prediction, rather than modeling the volatility as an underlying process.

4. Quantitative analysis

4.1 Summary Statistics

My goal is to estimate the prime rate process on an annual basis. I consider the prime rate values for the longest time period available. The sample period covers data from 1955 until 2024. The variables are not seasonally adjusted averages and were retrieved from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis; the data are freely available for download.

Table 1 reports the summary statistics of the CPI, 3-month Treasury bill: secondary market rate, effective federal funds rate, and bank prime loan rate. In addition, the prime rate's volatility, which is measured by the sample standard deviation, and the correlation between the variables and the prime rate are presented in Table 1. Observe the very high correlations of the T-Bill and the Funds Rate with the prime rate, 0.9557 and 0.9591 respectively. Likewise note that the CPI and the prime rate's volatility have high correlations of 0.7059 and 0.6261 respectively.

[Table 1 here]

4.2 Point estimate predictions

Table 2 presents the goodness-of-fit measurements for the out-of-sample predictions of the stochastic differential equations. R^2_{os} of the three proposed prime processes significantly outperform the four benchmark processes. Specifically, GPRIME (0.740) outperforms the closest benchmark, SABR (0.642), by approximately 9.8 percentage points. A t-test was performed to compare predictions between each prediction and the observed prime rate. The results reveal a significant difference in predictions between SABR and the prime rate (p-value = 0.0987) and CIR2 (p-value = 0.00023). For the remaining processes, the predictions are statistically indistinguishable from the observed prime rate. The F-Test compared each SDE prediction variance with the observed prime rate. The results indicate significant differences for Heston (p-value = 0.063) and HW2F (p-value = 0.000). For the remaining processes, prediction variances did not differ significantly from the prime rate variance.

In terms of accuracy, the RRMSPE confirms that all benchmark models exhibit significantly larger errors than the GPRIME, which attains the lowest RMSPE (0.0161). GPRIME particularly outperforms Heston (0.0197) by 22%, SABR (0.0189) by 17%, CIR2 (0.0214) by 33%. Furthermore, the HLN test confirms that GPRIME encompasses the predictions of the other stochastic differential equations. Furthermore, the AIC and BIC values are lowest for the GPRIME (-547.2 and -531.7, respectively). These results indicate that explicitly recognizing the macroeconomic transmission mechanism and the profit incentive is

important for predicting the prime rate's market structure. Indeed, these factors are more important than mean-reversion, value-of-information, and general interest rate processes.

With respect to the stability of the stochastic differential equations, GPRIME meets the 95% convergence rate criterion (0.971), whereas the Heston (0.809), HW2F (0.750), and CIR2 (0.912) models fail to converge. This failure to converge over time indicates structural instability in capturing the prime rate's dynamics. Although the SABR achieves convergence, (0.971), its predictive accuracy is inferior. Consequently, GPRIME demonstrates robust dominance across all metrics.

[Table 2 here]

Figure 5 presents the quantile-quantile plots of the predictions of each stochastic differential equation compared to the observed prime rate. The Q-Q plots provide visual confirmation of the proposed stochastic differential equations' out-of-sample fit. The four benchmark processes deviate significantly from the observed prime rate. This indicates a failure to capture the full process of the observed prime rate. In contrast, the three proposed processes closely follow the straight diagonal line; this indicates their distributional properties have a much better alignment with the observed prime rate data.

[Figure 5 here]

5. Conclusion

To specify the prime rate transmission mechanism, I propose a stochastic process that integrates financial markets and macroeconomic conditions. The process formulates the prime rate market by its incentive structure. In forming the underlying factors, I introduce

new stochastic processes that characterize the economic structure of mean-reversion (in contrast to the classic Vasicek process) and its forward-looking characteristic. Moreover, a continuous time delay process accounts for the delayed reaction of market participants to new information.

Analysis of the predictions demonstrates that recognizing the incentive structure within the transmission mechanism results in outperformance relative to benchmark processes. The numerical findings remain robust under several rigorous tests. Although mean-reversion and the value-of-information characteristics are notable, market profitability plays a greater role in the long-run than either. Thus, the analysis demonstrates that, if the aim of policymakers is to ensure financial stability, they should account for the commercial banking sector incentives. Hence, private business loan borrowers can account for the prime rate macroeconomy transmission effect.

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1. Figures and tables

Table 1. Summary statistics

The sample period statistics are annual from 1955 to 2024. Corr is the correlation of each variable with the prime rate over the whole sample period. CPI is the consumer price index. Volatility is the sample standard deviation of the prime rate. Observations denote the number of years within the sample period.

Variable Annual	Mean	Std	Min	q25	Median	q75	Max	Corr	Obs
Prime Rate	0.0681	0.0319	0.0316	0.0448	0.0622	0.0833	0.1887		70
T-Bill	0.0425	0.0302	0.0003	0.0196	0.0428	0.0578	0.1403	0.9557	70
Funds Rate	0.0464	0.0350	0.0008	0.0186	0.0433	0.0614	0.1638	0.9591	70
CPI	0.0361	0.0272	-0.0036	0.0168	0.0295	0.0429	0.1355	0.7059	70
Volatility	0.0080	0.0081	0.0000	0.0010	0.0047	0.0129	0.0288	0.6261	70

Table 2. Goodness of fit measurements

The sample consists of annual predictions during the period 1957-2024. Root mean square prediction error (RMSPE), and the relative root mean square prediction error (RRMSPE) are compared to the GPRIME, which has the smallest RMSPE. Convergence rate (CR) measures the convergence percentage over the entire simulation period. Bias is calculated as the average of each process prediction subtracted from the observed prime rate. F-test and t-test p-values are presented. HLN test statistic is reported and *P < 0.1, **P < 0.05, ***P < 0.01, testing the null hypothesis of forecast encompassing. R^2_{os} is the out-of-sample R^2. N is the number of predictions.

(a) Integrated	CR	RMSPE	RRMSPE	Bias	HLN	T-test	F-test	R^2_{os}	AIC	BIC	N
GPRIME	0.971	0.0161		-0.0003		0.863	0.850	0.740	-547.2	-531.7	68
IVPRIME	0.956	0.0163	1.0075	-0.0007	0.848	0.736	0.963	0.736	-546.2	-530.7	68
MRPRIME	0.956	0.0175	1.0112	-0.0007	0.769	0.712	0.987	0.734	-545.7	-530.2	68
(b) Benchmark	**CR**	**RMSPE**	**RRMSPE**	**Bias**	**HLN**	**T-test**	**F-test**	R^2_{os}	**AIC**	**BIC**	**N**
Heston	0.809	0.0197	1.220	0.0017	-1.365	0.491	0.063	0.613	-526.1	-525.7	68
HW2F	0.750	0.2131	13.20	-0.0161	-2.949	0.536	0.000	-44.35	-202.3	-201.8	68
SABR	0.971	0.0189	1.172	0.0038	-1.072	0.099	0.183	0.642	-531.6	-531.1	68
CIR2	0.912	0.0214	1.328	0.0086	-1.062	0.000	0.154	0.541	-514.6	-505.7	68

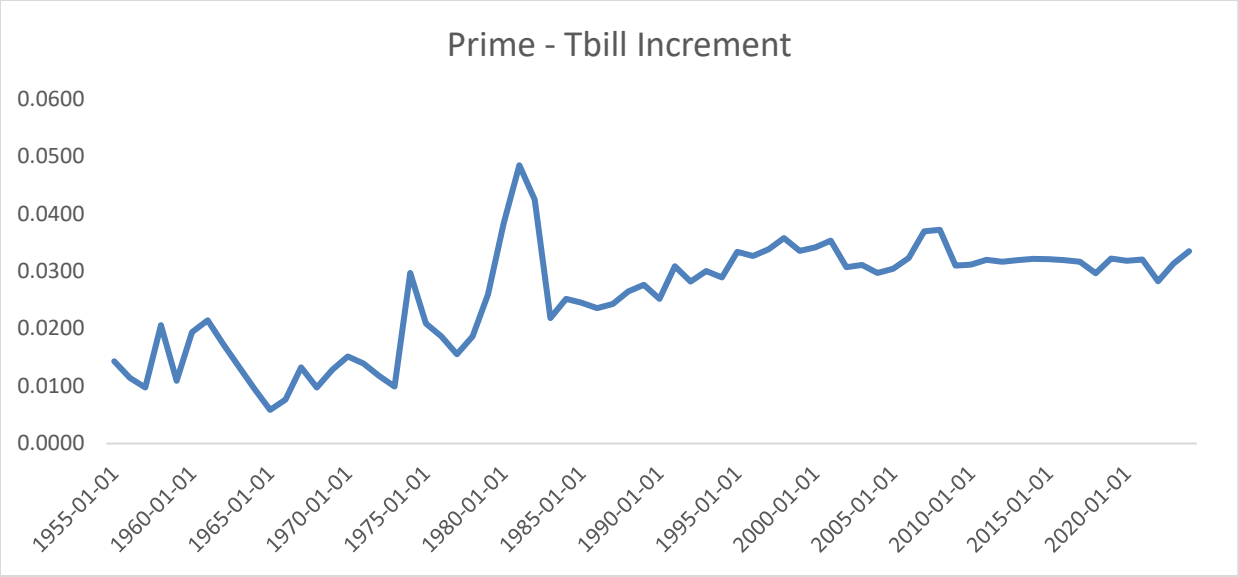


Figure 1. Investment Factor. This figure plots the mean increment between the prime rate and the three-month T-Bill. Annual data from 1955 to 2024. Data source: Federal Reserve Economic Data (FRED) database.

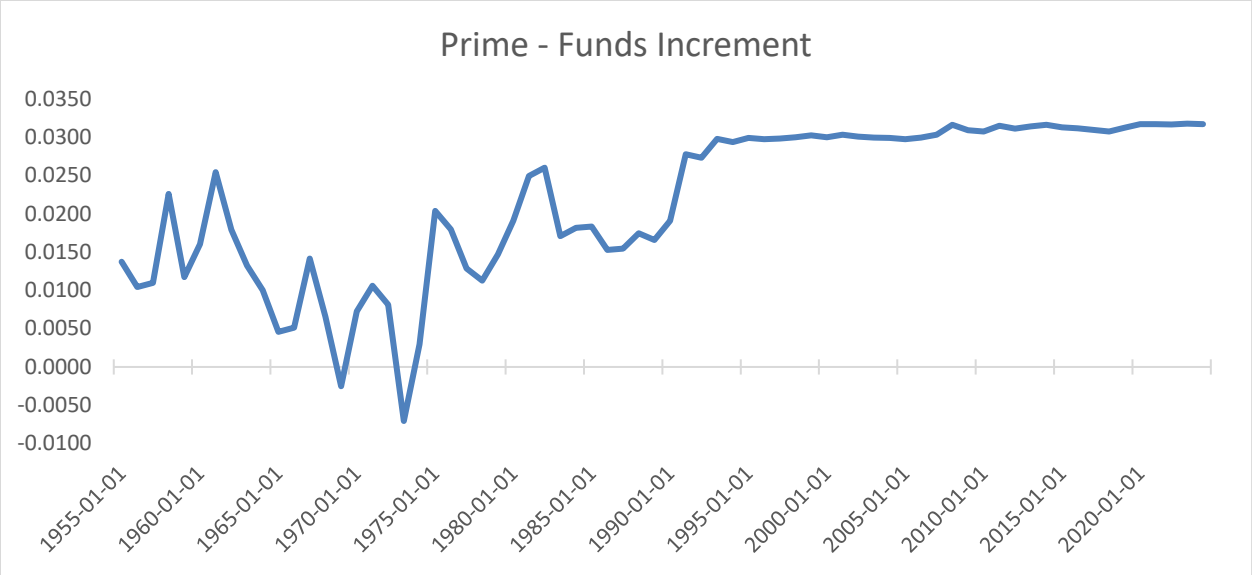


Figure 2. Funding Factor. This figure plots the mean increment between the prime rate and the funds rate. Annual data from 1955 to 2024. Data source: Federal Reserve Economic Data (FRED) database.

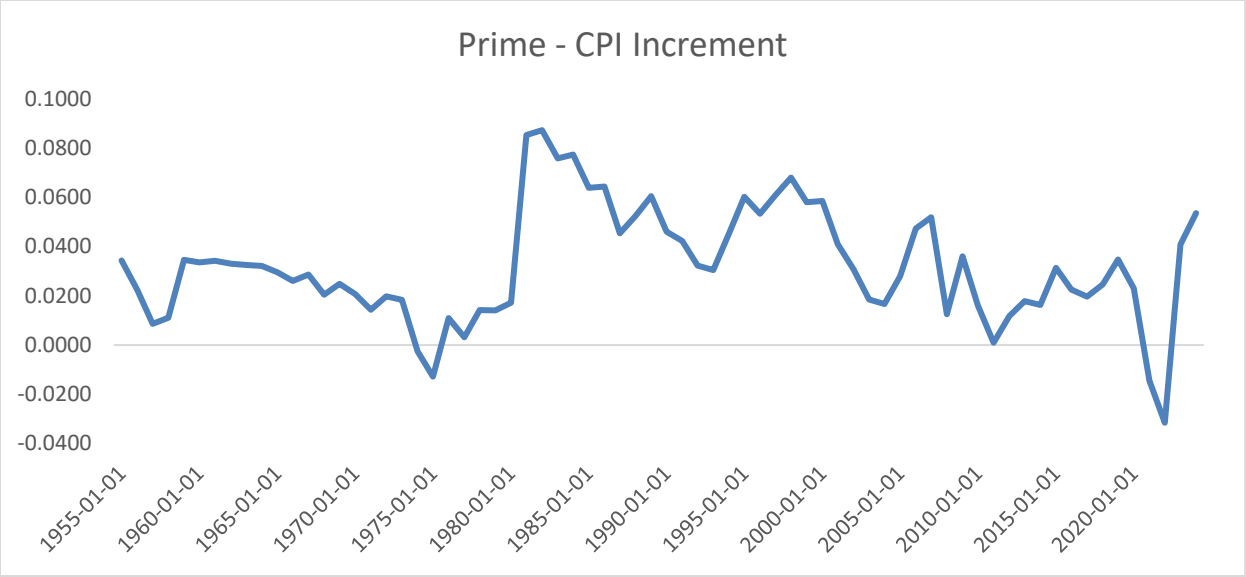


Figure 3. Inflation Risk Factor. This figure plots the mean increment between the prime rate and the CPI. Annual data from 1955 to 2024. Data source: Federal Reserve Economic Data (FRED) database.

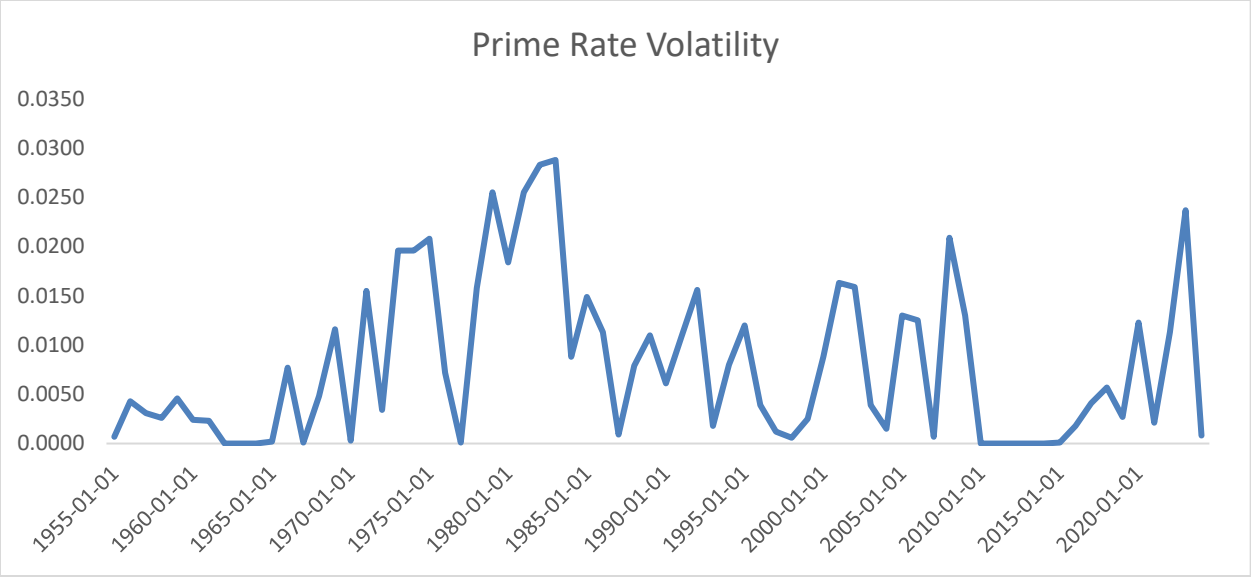


Figure 4. Volatility Risk Factor. This figure plots the volatility of the prime rate. Annual data from 1955 to 2024 are presented. The data were obtained from the Federal Reserve Economic Data (FRED) database.

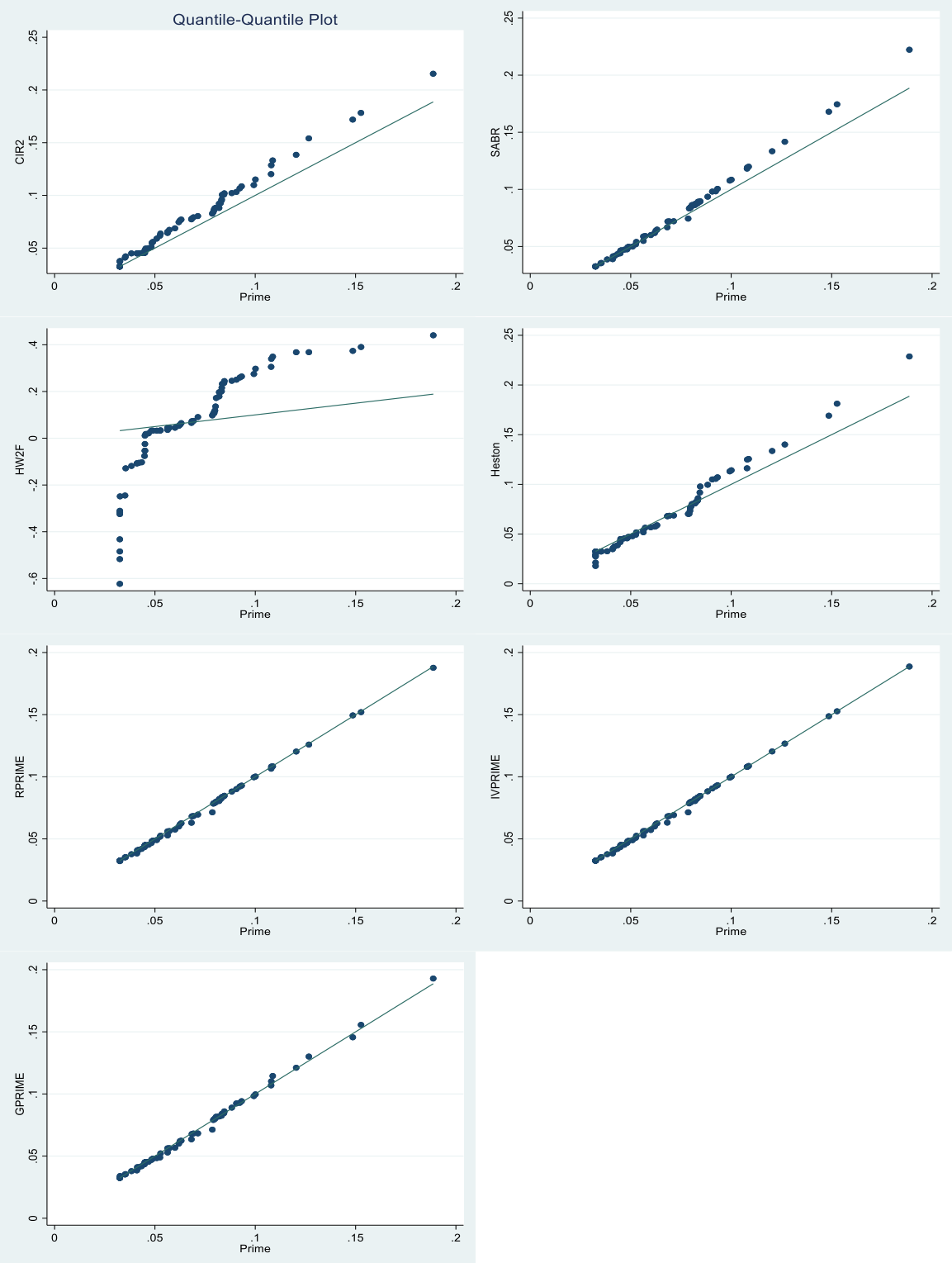


Figure 5. Q-Q plots. Compares each process's predictions, y-axis, to the observed prime rate, x-axis. Annual data, from 1957 to 2024.