

Dynamic Debt Runs: Evidence from a Structural Estimation*

Enrique Schroth[†] Gustavo Suarez[‡] Lucian A. Taylor[§]

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Abstract

We use data from the 2007 asset-backed commercial paper (ABCP) crisis to estimate a dynamic model of debt runs. The model features long-term investment financed with dispersedly held, short-term debt with staggered maturities. Yields change endogenously over time, which introduces dilution risk: lenders demand high yields to compensate them for being diluted by future lenders, which makes runs more likely. This model of fundamental-driven runs fits several features of the data, including the ten-fold increase in yield spreads leading up to runs, the high probability of recovering from a run, the positive relation between yield spreads and future runs, and the positive relation between yield levels and yield volatility. We measure the effectiveness of several policy interventions designed to prevent runs and find that interventions targeting asset liquidity and conduit leverage are most effective.

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[†]University of Amsterdam; enrique.schroth@uva.nl

[‡]Federal Reserve Board; Gustavo.A.Suarez@frb.gov

[§]University of Pennsylvania; luket@wharton.upenn.edu

Over the past few decades, traditional banks have increasingly transferred risks from their balance sheets to less-regulated financial institutions. Several authors have identified this trend as one of the major causes of the financial crisis of 2007 and 2008.¹ The reliance of such institutions on dispersed, short-term debt has resulted in runs by creditors, which has reignited the debate on how to eliminate runs and their associated costs.

The goal of this paper is to measure the fragility that results from financing long-term assets using dispersed, short-term debt. To do so, we structurally estimate a dynamic model of fundamental-driven debt runs using data from the 2007 asset-backed commercial paper (ABCP) crisis. The estimates allow us to measure the probability of a future run as a function of current leverage, asset liquidity, debt maturity, asset volatility, and other fundamentals. The structural approach allows us to evaluate several policy interventions designed to prevent runs.

ABCP conduits are off-balance sheet investment vehicles that banks use to invest in pools of medium- and long-term assets such as trade receivables and mortgages.² The conduit finances these investments by issuing short-term debt to dispersed creditors, rolling over its debt until it chooses to stop investing. The bank sponsoring the conduit typically provides a credit guarantee in the event that the conduit cannot roll over its debt.

The amount of ABCP outstanding in the U.S. contracted by roughly \$400 billion (one third) between August and December of 2007. Several authors have attributed this event to a run on debt.³ In a debt run, creditors refuse to roll over their debt not because the firm is insolvent, but because they fear other creditors will refuse to roll over. In the case of ABCP, roughly half

¹See, for example, Brunnermeier (2009), Gorton and Metrick (2010a), and Krishnamurthy (2009).

²The prevalent view is that ABCP conduits were essentially a way for sponsoring banks to take on systemic risk beyond regulations, without transferring the risk to ABCP investors. See Acharya and Richardson (2009), Acharya and Schnabl (2009), Acharya, Schnabl and Suarez (2010), Brunnermeier (2009) and Shin (2009).

³See, for instance, Covitz, Liang, and Suarez (2010), Acharya, Schnabl, and Suarez (2010), Gorton and Metrick (2010b), and Krishnamurthy, Nagel, and Orlov (2011).

of ABCP conduits had stopped rolling over maturing debt by the end of 2007. Creditors suffered losses in very few cases. Yield spreads on ABCP increased by a factor of ten and became very volatile leading up to the runs.

There are two main reasons why the ABCP crisis is a useful episode for measuring financial fragility. First, we can observe ABCP yields in great detail leading up to runs. Our data set merges credit reports by Moody’s Investors Service on all ABCP conduits since January of 2001 with a proprietary data set from the Depository Trust and Clearing Corporation (DTCC). The DTCC is a clearing house that provides daily data on the yield, maturity, size, and issuer’s identity for all U.S. ABCP transactions. Because yields adjust at each maturity date, the time series of yields measures the conduit’s health continuously and can potentially be an important lead indicator of runs. Second, as Krishnamurthy, Nagel, and Orlov (2011) argue, the 2007 run on ABCP was a central episode in the financial crisis:

“ [D]ata suggest that ABCP played a more significant role than the repo market in supporting both the expansion and contraction of the shadow banking sector. The repo market is significant, but it is a sideshow compared to the happenings in ABCP.”

Predicting debt runs and, therefore, the fragility of a financial institution is notably difficult. From an *ex post* perspective, we can learn what characteristics of a bank made it suffer runs. For example, Covitz, Liang, and Suarez (2009) show that most of the ABCP programs with weak credit guarantees by the sponsor suffered runs. Predicting runs *ex ante* is more challenging.⁴ Indeed, many programs with guaranteed commercial paper also suffered runs. Even in the simplest setup, the

⁴Runs in our model *can* be predicted. Therefore, we are ruling out the possibility of multiplicity of equilibria, as in Diamond and Dybvig (1983). As Gorton (1998) points out, multiplicity of equilibria leads to no empirical predictions. For example, the probability of a run cannot be linked to any fundamental information about the bank. Note, however, that our model, like most of the global games models used in the banking literature (see Goldstein (2011) for a survey), allows for the possibility of a ‘fundamentally driven panic,’ i.e., a situation where deteriorating fundamentals triggers a run on the bank even when the bank is solvent.

occurrence of a run must depend on leverage, the debt maturity structure, the asset growth rate and volatility, the liquidity of the underlying asset in the event of default, the quality of the conduit's credit guarantee, and, perhaps most importantly, on creditors' changing expectations that others may run. As noted by Calomiris and Mason (2003), the evaluation of the relative importance of these fundamentals, including the effects of liquidity, for generating runs requires a detailed model of bank failures. We propose a model that relates these fundamentals to endogenous leverage, yields, and runs.

Our model is based on He and Xiong (2011), which roughly resembles the ABCP design and captures the essential maturity mismatch between long-term assets and overlapping short-term liabilities. Our model preserves the main structure as theirs, whereby creditors track the time-varying 'fundamentals' of the program and run as soon as leverage crosses an endogenous threshold. Like their model, ours features a unique monotone equilibrium where creditors may run even when the firm is fundamentally solvent. The main difference, however, is that in our version the yield on short-term debt is not fixed but instead varies endogenously over time so that lenders break even when they roll over their debt. Indeed, one of the most salient features of the ABCP crisis is that ABCP yields increased exponentially before runs. To have a reasonable chance of fitting the data, and to predict runs, any structural model must make predictions about yields on ABCP.

We can observe most of the model's parameters directly in the data, but we must estimate three others by matching moments. The strength of the conduit's backup credit line is mainly identified off the fraction of runs that result in a recovery rather than default. We recover the asset's volatility from the endogenous volatility of ABCP yields. The asset's liquidity is mainly identified off average yields leading up to runs, and off the probability of future runs given current yields: higher liquidity reduces yields, which in turn makes future runs less likely. Without imposing the structure of a model, it is unclear how one could measure these economic primitives.

We find three main results. First, allowing yields to change over time makes runs more likely,

relative to He and Xiong's (2011) model with constant, exogenous yields. Using He and Xiong's (2011) calibrated parameter values, we find that runs are 2 to 11 times more likely in our model than in theirs. The reason, as He and Xiong (2011) conjecture, is that the conduit must offer high yields to induce rollover when conditions deteriorate. These high yields dilute all outstanding debt that matures later. Creditors preemptively demand higher yields to compensate them for the risk of future dilution. These higher yields in turn make leverage build up faster, which makes runs more likely. In short, this new risk, which we call 'dilution risk,' can be an important driver of yields and runs.

The second main result is that the model can fit several features of the 2007 ABCP crisis. In both actual and simulated data, roughly 55% of conduits that experience a run also experience a recovery within two months of the run. In the six months leading up to runs, average annual yield spreads increase from 5bp to 50bp. The model comes remarkably close to fitting the magnitude and timing of this run-up in yields. The model can also match both the overall level of ABCP yield volatility and the positive relation between yield volatility and the yield level. In both simulated and actual data, the current yield level helps to forecast whether a run will occur. However, the model currently predicts more runs than we see in the data.

These results on model fit contribute to the debate over what causes runs. The literature has been divided in two groups (see Goldstein (2011) for a survey). The first group, following Bryant (1980) and Diamond and Dybvig (1983), proposes that bank runs occur when panic makes creditors jump to the 'bad' equilibrium, self-fulfilling their expectations that all other creditors will run. The second group, motivated by Gorton's (1988) observation that panic-driven runs are impossible to detect, tries to establish that bank runs are caused by deteriorating fundamentals. In our model, as in Goldstein and Pauzner (2005), He and Xiong (2011), Morris and Shin (1998) or Vives (2011), deteriorating fundamentals cause creditors to run. Evidence in favor of the 'fundamental-

driven' runs hypothesis is still scant.⁵ The structural approach allows us to show that a model of fundamental-driven runs fits several features the 2007 ABCP crisis data, not just in terms of reduced-form, directional predictions, but also in terms of magnitudes.

The third main result relates to policy interventions designed to prevent runs. First, we show how regulators can use ABCP yields to detect the early warning signs of crises. For instance, given the conditions of the ABCP market in January of 2007, the model predicts that as soon as yield spreads reach 20bp, the probability of a run within the next three months is 35%. We then examine several policy-related counter-factuals. For instance, what would have happened to the ABCP market in 2007 had there been more backup credit from conduits' sponsors, stronger liquidity in the asset market, a lower federal funds rate, longer maturities on ABCP, or limits on leverage? We answer these questions by comparing simulated run probabilities between our calibrated model and a counter-factual model with altered parameter values. We measure the effects of policies implemented before crises (*ex ante* regulation) as well as during crises (*ex post* regulation). The policy levers that have the largest effects on runs are asset liquidity and initial leverage. Reducing the asset's illiquidity discount from 21% to 19% by, e.g., buying the distressed assets, lowers the probability of a run within 12 months from 56% to 22%. Therefore, providing liquidity for distressed assets effectively acts as deposit insurance for ABCP creditors. Reducing the conduit's initial leverage from 87% to 85% reduces that same probability from 56% to 20%. To our knowledge, this is the first paper to provide a quantitative policy analysis based on structural parameter estimates.

The paper is structured as follows. Section I describes the model and its assumptions. Section

⁵Calomiris and Mason (1997, 2003) use a rich set of determinants of bank solvency, including shocks to the aggregate, regional, and local economies to show that the Great Depression runs on banks belonging to the Federal Reserve System were not caused by panics. Chen, Goldstein and Jiang (2010) exploit the heterogeneity in mutual funds' asset liquidity to identify strategic complementarities and fragility from the sensitivity of mutual fund outflows to bad performance.

II presents the solution, and Section III discusses its predictions regarding yields and the likelihood of runs. Section IV describes the data, and Section V discusses the estimation of the model, paying special attention to the moments that identify the model’s parameters. Section VI describes our empirical results. Section VII contains the policy analysis, and Section VIII concludes.

I Model assumptions

We extend the model of He and Xiong (2011) by allowing yields on short-term debt to change over time with the value of the underlying asset. All assumptions below are shared with He and Xiong (2011) unless otherwise noted.

The model includes several features of ABCP conduits. The conduit finances a long-term asset using short-term, dispersed debt with overlapping maturities. The conduit must roll over this debt several times before the program ends, so the conduit faces rollover risk. The conduit’s sponsor provides imperfect credit support if the program cannot roll over its paper. The yield on newly issued debt adjusts over time in response to changes in fundamentals.

A Asset

At time zero an ABCP conduit, henceforth, the ‘firm’ or ‘program’, borrows \$1 to purchase a long-horizon asset. In reality, the ABCP conduit holds a pool of assets from different classes, the largest being trade receivables (14%), credit cards (12%) and auto loans (11%).⁶ The firm reinvests any interim cash flows from the asset. For example, the firm may buy new trade receivables using the payouts from maturing receivables. The firm therefore makes no net interim payouts to investors.⁷

⁶Table I shows a breakdown of ABCP assets by type.

⁷This assumption is made for parsimony. In He and Xiong (2011), the asset pays a fixed dividend, rdt , which is paid out in full to creditors as a coupon on the bond. Here, the face value of the zero-coupon debt can be converted into a fixed-coupon debt payment at any time, without the loss of generality. In practice, money market mutual funds, the main ABCP investors, value their holdings of commercial paper using amortized cost accounting, which

The asset produces a single net payout when the firm matures, which is when the conduit winds down. The firm matures with probability ϕdt in the interval $[t, t + dt]$, so the firm's expected time until maturity is always $1/\phi$. If maturity occurs at time τ_ϕ , the asset produces payout y_{τ_ϕ} , where y follows a geometric Brownian motion

$$\frac{dy_t}{y_t} = \mu dt + \sigma dZ_t. \quad (1)$$

Agents observe y_t at all times. All agents in the economy are risk neutral and have discount rate ρ , so the asset's value at time t is

$$F(y_t) \equiv E_t \left\{ \int_t^{\tau_\phi} e^{-\rho(s-t)} y_s ds \right\} = \frac{\phi}{\rho + \phi - \mu} y_t. \quad (2)$$

B Debt financing

The firm finances the asset by borrowing \$1 from a continuum of short-term creditors. The firm issues zero coupon debt with endogenous face value R_t .⁸ Each debt contract matures randomly and independently with probability δdt in the interval $[t, t + dt]$, implying that a debt contract's average remaining maturity always equals $1/\delta$. This modeling device, which follows Calvo (1983), Blanchard (1985), and Leland (1998), reflects that ABCP programs deliberately spread their debt maturities over time to reduce funding liquidity risk.

C Runs, liquidation, and credit guarantees

As payment for a maturing loan, lenders accept a new loan with a potentially different face value. If lenders choose not to roll over, we say that they run. We assume lenders roll over if they are indifferent between rolling and running. If lenders run and the firm cannot raise funds to pay off maturing lenders, then the firm defaults. In default, the firm sells the asset at a fraction α of its

effectively imputes a "coupon" payment to a zero-coupon security.

⁸In contrast, debt contracts in He and Xiong (2011) have face value normalized to one and offer exogenous interest rate r . In practice, commercial paper is a discount security that pays face value at maturity with no interim coupons.

fair market price, which yields

$$L(y_t) = \alpha F(y_t).$$

Parameter α measures the asset's liquidity. Consistent with industry practice, the firm distributes bankruptcy proceeds $L(y_t)$ to outstanding creditors in proportion to their face value.

An ABCP program's sponsor typically provides a credit guarantee that helps the program pay maturing lenders if the program is unable to issue new paper. Acharya, Schnabl, and Suarez (2010) show that the type and strength of credit guarantee varies across ABCP programs, and Covitz, Liang, and Suarez (2009) find that programs with weaker credit guarantees were more likely to experience runs in 2007.

We follow He and Xiong (2011) by modeling credit guarantees as an imperfect credit line from the sponsor. If the firm experiences a run, it pays off maturing paper by borrowing from the program sponsor at the prevailing rollover yield and maturity. The credit line therefore allows the firm to potentially survive a run long enough for the program to recover and begin issuing paper again. We assume the credit line fails independently, causing default, each instant with probability $\theta\delta dt$. Once a run starts, the credit line is expected to last for $1/(\theta\delta)$ years, so firms with higher values of θ have weaker credit guarantees.

D ABCP pricing

The firm issues debt with face value R_t per dollar loaned at time t . We can convert face values R_t (in units of dollars) to yields r_t (in units of fraction per year) using the relation⁹

$$r_t = (R_t - 1) \times (\phi + \delta). \tag{3}$$

⁹The yield r_t is the interest rate that delivers the same value as a zero-coupon bond with face value R_t , under the assumption that both bonds are paid back in full at $\tau = \min(\tau_\delta, \tau_\phi)$. Equation (3) follows from the condition

$$E_t \left\{ \int_t^\tau e^{-\rho(s-t)} r_t ds + e^{-\rho(\tau-t)} \right\} = E_t \left\{ e^{-\rho(\tau-t)} R_t \right\}.$$

Debt is priced in a competitive market so that creditors exactly break even. Specifically, the program sets its rollover face value R_t so that if creditors loan the firm \$1 at time t , they receive a debt contract worth \$1. Intuitively, if times are bad, the firm must issue paper at a high yield r_t to make creditors break even. If times are good, the new paper is almost risk free, and the new rollover yield will be close to the risk-free rate.

We assume the firm cannot or will not issue debt with face value above an exogenous cap, \bar{R} . Equivalently, rollover yields cannot exceed a cap \bar{r} (equation (3)). This is a critical assumption, as we show later that creditors run exactly when rollover yields hit this cap. There are a few rationales for assuming yields are capped.

The first rationale relates to credit guarantees. If the program's credit guarantee offers a backup credit line with yield \bar{r} , the conduit will optimally switch to this backup line as soon as market yields exceed \bar{r} . According to this interpretation, it is the firm that walks away from creditors in a run.

A second, related rationale is that \bar{r} reflects the sponsor's borrowing costs. The sponsor compares the costs of rolling over paper at the market rate versus triggering the credit guarantee, bringing the conduit back onto the sponsor's books, and paying off maturing lenders by borrowing at the sponsor's cost of capital. For example, a highly levered sponsor may let rollover yields go to a higher yield level \bar{r} before triggering the credit guarantee, because the sponsor's own borrowing costs are higher.

The third rationale relates to clientele. The main investors in ABCP are money market funds, which must invest in assets with very high short-term ratings (A1 by S&P or P1 by Moody's).¹⁰

¹⁰At the time of the 2007 crisis, rule 2a-7 under the Investment Company Act limited the portfolio share that registered money market mutual funds can invest in eligible securities not rated A1/P1 to 5% of the fund portfolio (these securities are typically rated at least A2/P2).

As an ABCP program's health declines and its rollover yields rise, eventually the program may lose its A1/P1 rating and its creditors will be unable to roll over its paper. Effectively, the program will be unable to roll over paper once yields exceed a cap. According to this interpretation, it is the creditors who walk away from the firm in a run.

A fourth rationale relates to the incentives of the ABCP program sponsor. If conditions worsen enough, rollover yields become so high that the ABCP program's equity is almost wiped out. Without enough equity, the sponsors have little incentive to keep running the program, so they may allow a run and rely on the credit guarantee.

The last rationale is that without a cap on yields, we cannot find an equilibrium with runs. Intuitively, no matter how bad conditions are, we can always make an infinitesimally small lender break even by promising him an extremely high face value. The high face value effectively transfers the entire firm to the lender by diluting previous lenders to nearly zero. Since the firm's value is always strictly positive, and since maturing lenders are infinitesimally small, we can always induce rollover by letting rollover yields go to infinity. This result is an artifact of the continuous-time setup. We suspect that a yield cap would arise endogenously in a more realistic model with non-infinitesimal lenders. The reason is that, once conditions get very bad, not even an infinite yield can make a larger lender break even.

II Model solution

First we solve for the dynamics of the firm's debt. Then we examine lenders' payoffs to derive the firm's value function. Next we solve for the dynamics of the state variable. We then find the condition that determines when lenders run. Finally, we solve for the equilibrium numerically. Details on the solution are in the Appendix.

A Debt dynamics

The total face value outstanding at time t , D_t , is given by:

$$D_t = R_0 e^{-\delta t} + \int_0^t D_s R_s e^{-\delta(t-s)} \delta ds. \quad (4)$$

This total face value includes paper issued at different past dates and yields. The first term reflects that the firm borrows \$1 at time zero, promises face value R_0 per dollar borrowed, and a fraction $\exp(-\delta t)$ of that initial debt has not yet matured as of time t . Since a fraction δds of face value D_s matures at instant s , the firm must pay maturing lenders the dollar amount $D_s \delta ds$, which it obtains by issuing new debt with total face value $(D_s \delta ds) R_s$. A fraction $\exp(-\delta(t-s))$ of that that time- s debt is still outstanding at time t . The properties of the Poisson process imply that all debt is equally likely to roll over in the next instant, regardless of when the debt originated. Therefore, D_t is also the average face value of debt rolling over at time t .

Taking derivatives of equation (4), the change in total face value at time t equals

$$dD_t = \delta D_t (R_t - 1) dt. \quad (5)$$

The first term reflects that the firm is issuing new debt, and the second term reflects that the firm is retiring some of the old face value.

The level of debt cannot decline, since debt is zero coupon and is rolled over. Face values R_t are high in bad times, which makes the firm's debt level rise quickly. In good times, R_t exceeds 1 by only a small amount, so the debt level rises more slowly.

B Lenders' payoffs

A lender receives a payout at time τ , which is the earliest of three events: program maturity, contract rollover, or default due to the failure of backup credit lines. That is,

$$\tau \equiv \min(\tau_\phi, \tau_\delta, \tau_\theta).$$

There are three possible scenarios a lender of vintage $s \leq \tau$ could find itself in:

1. The program matures at time $\tau = \tau_\phi$. The total proceeds are y_{τ_ϕ} so that an amount $\min(D_{\tau_\phi}, y_{\tau_\phi})$ is divided between the creditors. A lender with face value R_s will receive a fraction R_s/D_{τ_ϕ} of this amount, since lenders are paid in proportion to their face value. Therefore, for each dollar loaned at time s and not yet matured, the lender will receive a dollar amount

$$\frac{R_s}{D_{\tau_\phi}} \min(D_{\tau_\phi}, y_{\tau_\phi}) = R_s \min\left(1, \frac{y_{\tau_\phi}}{D_{\tau_\phi}}\right). \quad (6)$$

2. The firm defaults at time $\tau = \tau_\theta$ after other creditors run and backup credit lines fail. The asset is sold for

$$\tilde{L}(y_{\tau_\theta}) = \alpha \frac{\phi}{\rho + \phi - \mu} y_{\tau_\theta} \equiv l y_{\tau_\theta} \quad (7)$$

For each dollar loaned at time s and not yet matured, the lender will receive

$$\frac{R_s}{D_{\tau_\theta}} \min(D_{\tau_\theta}, l y_{\tau_\theta}) = R_s \min\left(1, l \frac{y_{\tau_\theta}}{D_{\tau_\theta}}\right). \quad (8)$$

3. The debt contract matures at time $\tau = \tau_\delta$. The lender chooses whether to roll over or run. As in He and Xiong (2011), a lender who runs gets paid back in full, because the amount of debt maturing at each instant is infinitesimally small and the firm's value is strictly positive. If the lender rolls over, the old loan is retired and a new loan is issued with face value R_{τ_δ} . The time- τ value of one dollar loaned at time $s \leq \tau$ is denoted $V(y_\tau, D_\tau, R_s; y^*)$, where y^* denotes creditors' running strategy. At $\tau = \tau_\delta$, the lender takes y^* as given, compares the value from running (R_s) to the value of rolling over ($R_s V$), and solves

$$\max_{\text{roll over or run}} \{R_s V(y_{\tau_\delta}, D_{\tau_\delta}, R_{\tau_\delta}; y^*), R_s\} = R_s \max_{\text{roll over or run}} \{V(\cdot), 1\}$$

C Value function

Each creditor's strategy consists of choosing y^* , a boundary for fundamental y_t below which they will run. The value at time t to a creditor who last loaned one dollar at time $s \leq t$ equals

$$\begin{aligned} V(y_t, D_t, R_s; y^*) &= E_t \left\{ e^{-\rho(\tau-t)} R_s \min \left(1, \frac{y_\tau}{D_\tau} \right) \mathbf{1}_{\{\tau=\tau_\phi\}} \right\} + \\ &E_t \left\{ e^{-\rho(\tau-t)} R_s \min \left(1, l \frac{y_\tau}{D_\tau} \right) \mathbf{1}_{\{\tau=\tau_\theta\}} \right\} + \\ &E_t \left\{ e^{-\rho(\tau-t)} R_s \max_{\text{rollover or run}} \left\{ V(y_{\tau_\delta}, D_{\tau_\delta}, R_{\tau_\delta}; y^*), 1 \right\} \mathbf{1}_{\{\tau=\tau_\delta\}} \right\}. \end{aligned} \quad (9)$$

We introduce the notation $x_t \equiv y_t/D_t$. Loosely speaking, x_t measures the inverse of firm leverage. Simplifying equation (9) yields

$$V(y_t, D_t, R_s; y^*) = R_s W(x_t; x^*) \quad (10)$$

$$\begin{aligned} W(x_t; x^*) &= E_t \left\{ e^{-\rho(\tau-t)} \min(1, x_\tau) \mathbf{1}_{\{\tau=\tau_\phi\}} \right\} + \\ &E_t \left\{ e^{-\rho(\tau-t)} \min(1, l x_\tau) \mathbf{1}_{\{\tau=\tau_\theta\}} \right\} + \\ &E_t \left\{ e^{-\rho(\tau-t)} \max_{\text{rollover or run}} \left\{ R_\tau W(x_\tau; x^*), 1 \right\} \mathbf{1}_{\{\tau=\tau_\delta\}} \right\}. \end{aligned} \quad (11)$$

The new function $W(x_t, x^*)$ is the value at time t to a creditor with one dollar of face value. This value does not depend on when the creditor last rolled over, due to the memoryless properties of the exponential distribution.

Applying Ito's Lemma and equation (5), it is straightforward to show that inverse leverage follows

$$\frac{dx_t}{x_t} = [\mu - \delta(R_t - 1)] dt + \sigma dZ_t. \quad (12)$$

Since the value function (11) and the dynamics of x_t are both functions of x_t only, then x_t is the only state variable of the problem. Face values depend only on x_t and not y_t and D_t individually. Also, maturing creditors decide whether to run by comparing the current value of inverse leverage

x_t to a threshold x^* . The model exhibits hysteresis: even if two firms started with the same initial fundamental y_0 and share the same current fundamental y_t , the firm that experienced lower intermediate realizations of y_s , for some $0 < s < t$, will have higher debt and hence higher yields and a higher probability of a run.

D Equilibrium loan prices and run threshold

Next we provide formulas for the face value, R_t . Investors break-even if for every \$1 invested in the firm at time t , they receive a loan worth \$1. That is, breaking even implies

$$1 = R_t W(x_t; x^*). \quad (13)$$

Since face values cannot exceed the cap, \bar{R} , the rollover face value is

$$R_t = \min(W(x_t; x^*)^{-1}, \bar{R}).$$

Following He and Xiong (2011), we focus on symmetric monotone equilibria: if all other investors use run threshold x^* , then an investor's optimal response is to use that same threshold. The following Proposition tells us how to find this threshold.

Proposition 1 *Let $R_t \equiv \min[\bar{R}, W(x_t; x^*)^{-1}]$. Then*

$$R_t = \begin{cases} W(x_t; x^*)^{-1} & \text{if } x_t > x^*, \\ \bar{R} = W(x_t; x^*)^{-1} & \text{if } x_t = x^* \\ \bar{R} & \text{if } x_t < x^*. \end{cases}$$

The proof to the Proposition is in the Appendix. The Proposition states that runs will not occur at face values R_t below the cap \bar{R} . The reason is that face values can still increase if they are below

their cap, potentially inducing the creditors to roll over the debt. The Proposition tells us to find the equilibrium run threshold x^* by finding the point $x_t = x^*$ where investors exactly break even at the capped face value:

$$\bar{R} = W(x^*; x^*)^{-1}.$$

The Appendix also contains the Hamilton-Jacobi-Bellman equation for this problem and also the numerical procedure for finding debt prices W and the equilibrium run threshold x^* .

III Model predictions

We highlight three predictions that illustrate how the model works and how our predictions differ from those in He and Xiong (2011). Since we lack closed-form solutions, we do not state model predictions as formal propositions. Instead, we illustrate predictions for specific parameter values.

A Yields and leverage around runs

Figure 1 illustrates how leverage and yields adjust over time. The top panel plots the time series of inverse leverage (x_t) for two simulated firms with the same initial fundamentals but different outcomes. The flat dotted line denotes x^* , the predicted run threshold. The dashed line depicts a firm whose assets grow steadily, so the firm never experiences a run. The solid line shows a firm that experiences two runs when its inverse leverage falls below x^* . During the first run, credit lines survive long enough for the firm to recover and begin issuing paper again. Credit lines fail in the second run, causing the firm to default and liquidate assets.

The bottom panel shows rollover yields for those same simulated firms. Since the firm represented by the red dashed line remains healthy, its yield remains at or near $\rho = 5\%$. The yields of the firm represented by the solid blue line spike up and become more volatile as a run becomes

imminent, eventually reaching the cap \bar{r} when the run begins. As soon as this firm recovers from its first run, yields drop below the cap.

B Runs and solvency

Like He and Xiong (2011), we find that creditors run on solvent firms but not on “super-solvent” firms. Solvent firms are those where the asset’s market value, $F(y_t)$, exceeds the amount owed to creditors, D_t . Super-solvent firms are those where the asset’s fire-sale value, $\alpha F(y_t)$, exceeds D_t .¹¹ In other words, creditors will not run on a firm that has enough assets to pay off all lenders in the event that the firm defaults and has to sell the asset at a fire sale discount. In sum, extending He and Xiong’s (2011) model to allow time-varying yields does not significantly affect the relation between runs and solvency.

C Flexible pricing, dilution risk, and the likelihood of runs

In contrast, allowing time-varying yields makes runs significantly more likely, relative to He and Xiong’s (2011) model with constant yields. We compare predicted run probabilities in our model and He and Xiong’s (2011) model (henceforth, HX). The following assumptions make the models comparable. First, we use HX’s calibrated parameter values and initial conditions in both models. Second, at time zero the firm buys an asset, and this asset’s market value is the same in both

¹¹The supersolvency threshold is at $x^{**} = \frac{\rho + \phi - \mu}{\alpha \phi}$. It is straightforward to show that if the run threshold x^* exceeds x^{**} , then the analytical solution for W (the market value of \$1 of face value) decreases in x for some values $x < x^*$. Since it is economically implausible that debt becomes less valuable when the fundamental improves, it must be the case that the run threshold is below the super-solvency threshold.

models.¹² Third, the firm borrows \$1 at time zero to buy this asset in both models.¹³ In HX lenders are offered a face value of \$1 with exogenous yield r . In our model lenders are offered the market yield at which they break even. These assumptions still leave two parameters free: r (the yield in HX) and \bar{r} (the yield cap in our model). We show predictions for a range of r and \bar{r} values.¹⁴

Results are in Table II. Panel A shows the fraction of simulated firms that experience a run within one year in our model, divided by the same fraction in HX’s model. We find that runs are between 1.93 and 11.16 times more likely in our model than in HX. Runs are especially more likely in our model if the exogenous interest rate r is higher in HX, because investors are less willing to run in HX if debt offers a higher interest rate. Runs are also relatively more likely in our model if we use a lower yield cap \bar{r} , because a lower cap leaves less room for adjustment when conditions worsen. Of course, we do not claim that these results hold for all possible parameter values.

Next we explain the mechanics and then the intuition behind this result. Panels B and C help explain why runs are more likely when yields are flexible. In both models, the likelihood of a run depends on (1) where the run threshold is, (2) where the state variable starts, and (3) the state variable’s dynamics. We examine each channel in turn.

¹²The asset pays interim cash flows at rate r in He and Xiong (2011), but our model has no interim cash flows. Setting the asset’s value equal in the two models requires choosing initial fundamental y_0 by solving

$$\begin{aligned} F^{HX}(y_o^{HX}) &= F(y_0) \\ \frac{r}{\rho + \phi} + y_o^{HX} \frac{\phi}{\rho + \phi - \mu} &= y_0 \frac{\phi}{\rho + \phi - \mu}, \end{aligned}$$

where $y_o^{HX} = 1.41$ is the initial fundamental in He and Xiong (2011), and y_0 is the initial fundamental in our model.

¹³Face value is assumed equal to \$1 in He and Xiong (2011). Face value equals $D_0 = R(x_0; x^*)$ in our model, so the state variable’s initial condition in our model is determined by $x_0 = y_0/R(x_0; x^*)$.

¹⁴Our values of r are centered at the calibrated value of He and Xiong (2011). We choose values of \bar{r} much higher than r , because higher values of \bar{r} make runs *less* likely in our model, all else equal. We find that despite these high \bar{r} values, runs are still *more* likely in our model than in He and Xiong (2011).

First, Panel B shows that the run threshold in our model is between 1.56 and 2 times larger than in HX. All else equal, this higher threshold will tend to make runs more likely in our model.

Second, Panel C compares the firm’s initial market leverage (market value of debt divided by market value of asset) in the two models. Initial leverage is only 71-86% as high in our model as in HX. Although the initial asset value is the same in both models, debt initially has a lower market value in our model: lenders initially borrow \$1 at a low market interest rate in our model, whereas they borrow at the higher exogenous rate r in HX. The lower initial leverage means our state variable’s initial value is higher,¹⁵ which by itself will make runs less likely in our model. Since we find overall that runs are more likely in our model, it must be that this initial leverage effect is outweighed by the other two effects.

Third, state variable dynamics (i.e. leverage dynamics) tend to make runs more likely in our model. Comparing formulas for state variable dynamics in the two models, one can show that inverse book leverage has exactly the same volatility in both models, but the drift rate is lower in our model.¹⁶ The lower drift rate pulls the firm toward the run threshold, making runs more likely in our model.

Intuitively, flexible yields make runs more likely because they introduce a new risk, which we call “dilution risk,” on top of rollover risk and insolvency risk. If conditions worsen for a firm, the firm will have to offer higher yields to induce rollover. These higher yields increase the firm’s debt by more, which dilutes the stakes of other lenders. This effect depends strongly on the assumption that priority in bankruptcy is according to face value and not seniority, which matches ABCP

¹⁵More formally, if the firm initially borrows at the risk-free rate ρ in our model, then we can show that

$$x_0 = \frac{y_0^{HX} + \frac{r}{\phi} \left(1 - \frac{\mu}{\rho + \phi}\right)}{1 + \frac{\rho}{\delta + \phi}},$$

where x_0 is the initial state variable in our model, and y_0^{HX} is the initial state variable in HX.

¹⁶The state variable x_t in our model follows equation (12). The state variable in HX follows equation (1).

market practice. A lender deciding whether to roll over in our model anticipates the possibility of being diluted in the future if conditions worsen. The lender therefore preemptively demands a higher yield to compensate him for dilution risk. These higher yields make the firm's leverage increase faster, pulling the firm toward the run threshold. The higher yields also result in a higher run threshold, because yields hit their cap at higher values of x , i.e., at a lower leverage.

IV Data

The data we use to estimate our model come from several sources. We obtain data on all issuance transactions in the U.S. ABCP market from 2001-2010 from the Depository Trust and Clearing Corporation (DTCC). We complement these data with Moody's ratings of each ABCP program. As in Covitz, Liang and Suarez (2009) or Acharya, Schnabl and Suarez (2010), we are able to observe each ABCP program's portfolio by asset type, and also observe the program's sponsors and type of guarantees to creditors. We observe every debt issue by each ABCP conduit, allowing us to construct the distribution of maturities and rollover yields of all outstanding ABCP debt. We also use Barclay's price index data on the main asset classes that ABCP programs purchase.

Using data collected from ABCP program reports by Moody's Investors Service, we classify the type of guarantee provided by the conduit sponsor to protect program investors. The categories we use are: full credit guarantee, when the sponsor provides a line that can be drawn regardless of asset defaults; a full liquidity guarantee, in which a sponsor provides a line that can be drawn as long as assets are not in default; a structured investment vehicle (SIV) guarantee, in which only a portion of conduit liabilities are covered by the line; and extendible paper, in which issuers have the option of extending the maturity of the paper at a pre-specified penalty rate (Acharya, Schnabl, and Suarez (2010)).

Table I shows the proportion of ABCP programs' assets in different classes as of August 2007, at

the onset of the run on the ABCP market. The largest asset classes were trade receivables (14%), credit card receivables (12%), auto loans (11%), and “securities” (11%). Surprisingly, mortgages made up just 9% of ABCP assets, although the “securities” category may contain mortgage securities.

We use the method of Covitz, Liang, and Suarez (2009) to identify runs in the data. We say that program i is in a run in week t if either (1) more than 10% of the program’s outstanding paper is scheduled to mature, yet the program does not issue new paper; or (2) the program was in a run in week $t - 1$ and the program does not issue new paper in week t . A program recovers from a run in week t if it issues paper in week t but was in a run in week $t - 1$.

We measure each program’s rollover spread as the dollar-weighted average annual yield for paper issued on Thursday¹⁷ of week t , minus the prevailing federal funds rate. If the program did not issue paper on Thursday, we move one day ahead until finding an issuance transaction in week t .

Covitz, Liang, and Suarez (2009) show that the total amount of ABCP outstanding increased gradually in 2007 through the end of July, when it peaked near \$1.2 trillion. At that time there were 339 ABCP programs operating. Yield spreads averaged 5bp in the first half of the year. In August 2007, the amount of debt outstanding plunged by \$190 billion and average spreads increased to 74 basis points.¹⁸ Roughly 25% of ABCP programs experienced a run in August, according to our measure. By the end of the year, 40% of ABCP programs were experiencing a run, and the total amount of ABCP outstanding was 30% below its mid-year peak. Rollover yields remained high and volatile in the second half of 2007. Although many ABCP programs experienced runs in 2007, investors took losses at only 6 ABCP programs (Acharya, Schnabl, and Suarez (2010)). The

¹⁷We choose Thursday because amounts outstanding are measured at the end of Wednesday each week.

¹⁸Important events in early August 2007 include American Home Mortgage’s declaration of bankruptcy (Aug. 6), the suspension of three subprime mortgage funds at BNP Paribas (Aug. 9), emergency liquidity provision by the ECB (Aug. 9) and the Federal Reserve (Aug. 10), and the granting of an emergency loan to Countrywide Financial (Aug. 15).

vast majority of programs were able to rely on credit guarantees to pay off maturing paper in full. It is unclear whether investors expected credit guarantees to be so strong.

In our initial analysis we use data on runs and spreads from 2007 only. We face the trade-off that a larger sample provides more precise estimates, but it is harder to argue that model parameters are constant over a longer time horizon. Year 2007 is an ideal sample because it contains many runs and also several months of pre-run data.

V Estimation

Some of the model's parameters can be measured directly from the data. We estimate the remaining parameters by matching the model's simulated moments to the empirical moments in the ABCP data.

A Observable parameters

1. Risk-free rate

Investors' discount rate ρ is also the risk-free interest rate. We set ρ to 4.9%, the annualized yield of one-month T-bills at the beginning of 2007.

2. Debt maturity

The average debt maturity in our model is $1/\delta$. We set $1/\delta$ to 37 days, the average maturity of ABCP as of March of 2007. The assumption that δ is constant may be problematic given that most programs experienced a rat-race whereby they offered shorter rollover maturities to prevent creditors from running (Brunnermeier and Ohmke (2010)). However, maturities were shortened to a minimum of about one month, on average, at least 25 weeks before runs occurred. In fact, maturities stabilized before yields started to adjust upwards (results available on request).

3. Program maturity

The average program life span in our model is $1/\phi$. If we add the assumption that new ABCP programs are created at a constant rate, then the model predicts that the average age of programs alive at any time t equals $1/\phi$. The average age of ABCP programs as of July, 2011 is 9.7 years.¹⁹ Therefore, we set ϕ to $1/9.7 = 0.103$.

4. Fundamental drift rate

Equation (2) implies that μ , the asset's drift rate, is also the asset's expected return. We set μ to the estimated expected return on the average portfolio of ABCP assets.²⁰ We estimate the expected return for each asset class ABCP programs hold (e.g. credit card receivables), then compute a weighted-average using Société Générale's portfolio holdings for the ABCP industry in August 2007.²¹ We estimate each asset class's expected return following the method of Fama and French (1993). Specifically, for each asset class we estimate a time-series regression of the asset class's realized monthly excess return (from Barclay's) on three risk factors: *TERM*, *DEF_HY*, and *DEF_IG*. *TERM* is the difference between the long-term government bond return and the monthly T-bill rate, both from CRSP. *DEF_HY* (*DEF_IG*) is the difference between the return on Barclay's U.S. long corporate high yield (investment grade) bond portfolio and the long-term government bond return. An asset class's expected return is then the risk-free rate plus its risk premium, which is the sum of its factor loadings times their respective risk premia. Estimated factor loadings, risk premia, and portfolio weights are in Table I. Our estimate of μ is 6.1%, which is 1.2 percentage points above the risk-free rate.

¹⁹We need to confirm that the average age at the beginning of our sample was stable over time.

²⁰Eventually we hope to measure program-specific expected returns, since we know each program's portfolio by asset type.

²¹"The ABC's of ABCP," Société Générale (2008).

5. Yield caps

Program i 's yield cap, \bar{r}_i , is observed for all programs that experienced runs. Indeed, for any program with a run, \bar{r}_i equals the last observed yield before the run starts. For programs that never experience a run, the maximum observed yield r_j^{\max} is only a lower bound on \bar{r}_j . Therefore, we use the observed yield caps to extrapolate the unobserved ones. We estimate \bar{r}_j for all programs that do not experience runs from

$$\widehat{\bar{r}}_j = \max \left\{ r_j^{\max}, r_t^f + \mathbf{x}_j \widehat{\boldsymbol{\gamma}}' \right\},$$

where r_t^f is the risk-free rate, \mathbf{x}_j is a vector of program-specific determinants of the cap, and $\widehat{\boldsymbol{\gamma}}$ contains estimated coefficients from the OLS regression

$$\bar{r}_i - r_t^f = \mathbf{x}_i \boldsymbol{\gamma}' + \varepsilon_i,$$

for all programs i that experience runs. If program i experienced multiple runs, we set \bar{r}_i to the average pre-run spread across its runs. In \mathbf{x}_i we include the following explanatory variables for yield caps:

- Dummies for the program guarantee type, i.e., $I\{\text{full liquidity?}\}$, $I\{\text{extendible notes?}\}$, and $I\{\text{SIV?}\}$ to capture the fact that programs with stronger support from the sponsor may prefer to delay the run instead of facing losses;²²
- sponsoring bank fixed effects, to proxy for the differences across sponsors in the ability to meet the liquidity requirements of a run.

We winsorize the estimated yield cap spreads $(\bar{r}_i - r_t^f)$ at the 5th and 95th percentiles. Giving equal weight to all programs, including programs that never experienced runs, the average yield cap in excess of the risk free rate is 0.65%, with standard deviation 0.26%.

²²Full credit support is the excluded category.

B Identification of remaining parameters

The remaining parameters to estimate are σ (fundamental volatility), θ (the weakness of credit guarantees), and α (asset liquidity). We cannot identify program-specific parameter values, because we would need as many moment conditions as programs. Instead, we estimate the model within subsamples where parameters are reasonably constant across observations. An alternate approach is to make each parameter a function of observable program characteristics, then estimate the dependence of parameters on those characteristics.

We estimate parameters using the simulated method of moments (SMM). This estimator chooses parameter values that minimize the distance between moments generated by the model and their sample analogs. Since we lack closed-form solutions, we estimate model-implied moments from simulated data. Below we define the four sets of moments used in our estimation procedure. We also provide intuition for how the moments help identify each parameter. All moments depend on all parameters, but we highlight the moments that matter most in identifying each parameter.

1. Credit line strength

The moment most informative about θ (the weakness of credit guarantees) is $M_1(\tau)$, defined as the fraction of runs that are followed by a recovery (i.e. debt issuance) within τ , for $\tau = 1, \dots, 8$ weeks. Simulated values of M_1 are in Figure 2. We see that lowering θ increases the probability of recovering from a run. Intuitively, a stronger credit guarantee (i.e. lower θ) buys the conduit time for fundamentals to improve, so the conduit can exit the run before defaulting.

2. Fundamental volatility

Fundamental volatility σ is mainly identified off yield volatility. Predicted yield volatility is

$$var_t(dr_t) = \left(x_t \frac{\partial r}{\partial x}(x_t) \right)^2 \sigma^2. \quad (14)$$

Since yield volatility depends directly on fundamental volatility σ , there is hope of recovering the value of σ from data on yield volatility. The first term in (14) increases in the level of yields, so the model predicts that yield volatility is high when the level of yields is high.²³ The model therefore produces time-varying volatility in yields, even though fundamental volatility is constant.

M_2 is the moment we use to measure yield volatility. Specifically, M_2 is a 3×1 vector containing the conditional variance of one-week changes in normalized yields \tilde{r}_{it} :

$$M_2(b) \equiv \text{var} [\tilde{r}_{it+1} - \tilde{r}_{it} | \tilde{r}_{it} \in b], \text{ for } b = 2, 3, 4$$

$$\tilde{r}_{it} \equiv \frac{r_{it} - r_{ft}}{\bar{r}_i - r_{ft}} \in [0, 1].$$

We normalize yields in order to sweep out time-series variation in the risk-free rate r_{ft} and cross-sectional variation in yield caps \bar{r}_i . Normalized yields are mechanically in $[0,1]$. We split the interval $[0,1]$ into four bins, b , of length $1/4$, and we assign each observation it into the bin containing \tilde{r}_{it} . We use bins so that yield volatility can vary with the level of yields, as the model predicts. We throw out bin 1 (spreads close to zero), because yield volatility in this bin is sensitive to the choice of initial condition x_0 in our simulations, and we want moments that do not depend on x_0 .

3. Asset liquidity

Having identified σ and θ , we identify asset liquidity α off of conditional run probabilities, and off the pattern of yields leading up to runs. Moment M_3 is a 3×15 matrix containing the probability of a run within τ weeks ($\tau = 1, \dots, 15$), conditional on the program's normalized yield being in bin b ($b = 2, 3, 4$) today. This moment helps identify α , because run probabilities are very sensitive to

²³In our numerical exercises we find that as x decreases, the increase in slope more than offsets the decrease in x , so that indeed yield volatility increases as x drops.

liquidity. For example, Table IV (discussed in Section 7) shows that increasing α from 0.79 to 0.81 reduces the probability of a run within 3 months from 31% to 3%. The reason is that higher asset liquidity reduces debt yields: a higher α means recovery rates in default are higher, so lenders do not need such high yields to break even. Lower yields make leverage grow more slowly over time, and also make yields hit their cap at a higher leverage level, both of which make runs less likely.

Whereas M_3 contains information on future runs conditional on yields, M_4 contains information on yields conditional on future runs. Specifically, M_4 is the average yield spread in each of the 26 weeks leading up to a run. This moment adds the additional restriction that the model not only matches the probability of a run conditional on yields, but that these actual run probabilities are consistent with the average yields.

VI Empirical results

A Model calibration

In this section we evaluate how well the model fits the data by calibrating the parameters θ, σ and α . For the calibration, we set the observable parameters to the baseline values below:

$$\mu = 0.061, \delta = 9.872, \phi = 0.103, \rho = 0.049, \bar{r} = 0.06. \quad (15)$$

For now we assume that θ, α and σ are constant across programs. In future drafts we allow these parameters to vary with program characteristics such as the type of credit guarantee.

Figure 3 shows the actual and simulated $M_1(\tau)$, i.e., the probability that a program experiencing a run recovers within τ weeks. For $\theta = 0.78$, the predicted recovery probability matches closely the actual probability within 2 and 3 weeks of the start of the run. The predicted recovery probability is also within the 95% confidence interval of the actual average probability up to 5 weeks after the

average run starts, and very close to this interval thereafter. This value of θ implies that the average ABCP sponsor could provide back-up credit for almost 7 weeks on average.²⁴

Table III shows the results of calibrating σ to M_2 , the conditional volatility of ABCP yields. For $\sigma = 0.044$, the simulated volatility is very close to the actual volatility in all the yield bins: if slightly lower, the simulated volatility is within the 95% confidence interval of the actual volatility in bins 1 through 3, and within the 90% confidence interval in bin 4. In both simulated and actual data, yield volatility increases in the level of yields. Moreover, the simulated yield volatility also matches the observed concavity of the actual yield volatility across yield bins. This concavity is due to a selection effect: as the yield increases, more programs are likely to enter a run one week later, and we cannot include these observations when computing M_2 . The calibrated $\sigma = 4.4\%$ is a measure of the model-implied volatility of the assets held by the average ABCP program. This estimate is remarkably close to the actual annualized volatility of daily changes in the ABX mortgage index through the first quarter of 2007 (30 bp per day, or 5.7% per year).²⁵

Figures 4 and 5 show the calibration of α through the yield levels in event time (M_4) and the conditional run probabilities (M_3), respectively. For $\alpha = 0.785$, simulated rollover yield spreads leading up to runs are within in the 95% empirical confidence intervals between event weeks -12 and -2 leading to the run. Otherwise, the model's predicted yield is close to but higher than the actual yield.

Figure 5 shows that, in both the actual and simulated data, spreads predict runs: a high yield spread today is associated with a higher chance of a run 1 to 15 weeks in the future. However, the model predicts more runs than we see in the data. For example, the model's predicted run probabilities when the spread is 15 to 25bp match the actual ones when the actual spread is above

²⁴Once a run starts, the average time until default is $1/(\theta\delta) = 6.75$ weeks.

²⁵The ABX index we use tracks the cost of insurance against default on MBS backed by AAA tranches of mortgages originated in the second half of 2006.

40 bp. Below we address this issue by allowing for heterogeneity in the unobservable parameters, estimating the model in different subsamples of ABCP programs.

B Estimation

[To be completed.]

VII Policy analysis

As in Rochet and Vives (2004) and Vives (2011), we can derive policy recommendations based on our model's equilibrium relationship between fundamentals and runs. Our estimates of the model's parameters allow us to conduct two types of counter-factual analysis. First, we examine how to regulate conduits *ex ante* (i.e., before crises begin) in order to reduce the probability of runs in the distant future. For instance, we measure the effect on future runs of setting limits on new conduits' initial leverage. Second, we examine how to effectively control the run probability *ex post*, i.e., once the regulator sees warning signs about a conduit's health. Before turning to these counter-factual analyses, we describe the warning signs regulators can use to gauge the probability of a future run.

A What are the warning signs?

Figure 6 plots the simulated probability of a run within 3, 6 and 12 months as a function of the ABCP conduit's current leverage (top panel) and rollover yield spread (bottom panel). The top panel shows that the probability of a future run is strongly increasing in the conduit's current leverage. An increase in leverage from 87 to 88% increases the probability of a run within three months from roughly 20 to 40%. The bottom panel shows that the current rollover yield is also a strong predictor of runs: an increase in rollover spreads from 20 to 40bp signals an increase in the probability of a run within 3 months from 35% to 55%.

B *Ex ante* regulation

Table IV shows the estimated probabilities of a run on an average ABCP program given small changes in the model’s parameters. The base case run probabilities are calculated using the known parameter values in (15) and the calibrated values above for the unknown parameters i.e., $\theta = 0.78$, $\alpha = 0.785$ and $\sigma = 0.044$. We set initial leverage, $1/x_0$, to 0.87 to capture conditions at the beginning of 2007; this value of $1/x_0$ implies that 56% of simulated conduits experience runs in 2007, which matches the observed fraction.

Runs are most sensitive to the program’s initial leverage. An decrease in initial leverage from 0.874 to 0.85 decreases the run probability to 0.2 within one year, and to a very low probability of 0.02 within three months. Similarly, a relatively small decrease in the asset’s liquidation discount from the estimated 22.5% to 19.5% also reduces the run probability by more than half within one year (to 0.22) and by more than 90% (to less than 0.03) in three months.

Surprisingly, an increase in the asset’s expected maturity makes runs significantly less likely: a one year increase in the expected maturity decreases the run probability to 0.09 within the next month and to 0.35 within the next year. An increase in asset maturity while keeping debt maturity fixed could be interpreted as a worsening of the mismatch between assets and liabilities. In this model, however, because creditors always have the option to run, then longer maturities of assets relative to liabilities increase the creditor’s upside in high states. For very short debt maturities, this effect could be potentially very strong, as our estimates confirm. Consistent with this interpretation, shortening the average debt maturity to 29 days also reduces the run probabilities, especially within the three and six month horizon. Indeed, shorter maturities imply a lower threshold for runs and lower yield spreads.

Table IV also shows the results of simulating tighter controls on the quality of assets that ABCP programs can buy. An increase in the asset’s growth rate while keeping the volatility constant, or

a decrease in the asset’s volatility while keeping returns constant, will also significantly reduce the run probabilities.

Finally, the risk of a run is not as sensitive to the risk free rate, the cap on rollover yields, nor the strength of the credit line. The insensitivity of runs to the strength of credit lines is likely due to the fact that most programs had strong back-up credit lines. As shown by Acharya, Schnabl and Suarez (2010), a majority of the commercial paper outstanding was fully guaranteed by the conduit’s sponsor. Therefore, while the few programs with very weak guarantees experienced runs, several programs with strong credit lines did, too.

We conclude from this exercise that the main determinants of runs on ABCP conduits are the conduit’s initial leverage and the expected fire-sale discount in case the asset is liquidated prematurely. A regulator can more effectively prevent runs by setting minimal leverage requirements or by improving the distressed asset’s liquidity.

C *Ex post* regulation

Table V evaluates the effectiveness of four different policy interventions as the conduit begins getting in trouble, i.e., as leverage and yield spreads increase. Consider first a reduction in the discount from a premature sale of the illiquid asset, e.g., an increase in α resulting from the regulator providing liquidity by purchasing the distressed assets. An increase in α from the estimated 0.785 to 0.81 when yield spreads are only 27.5 bp would decrease the run probability from 0.46 to 0.05. More strikingly, the same liquidity provision intervention is still effective when spreads reach 82.5 bp, reducing the run probability from 0.83 to 0.14. The main intuition for this result is that the ultimate reason why creditors run is the fear that the asset has to be liquidated at a discount before they roll over their debt. An increase in α effectively acts as deposit insurance for ABCP creditors.

Table V also shows that the conditional probability of a run is sensitive to changes in the yield cap, \bar{r} . An increase in the yield cap from the observed average of 6% to 6.2% decreases the run

probability to 0.44 when yield spreads are 27.5bp and to 0.81 from 0.83 when spreads reach 82.5 bp. While the yield cap does not have significant effects *ex ante*, it still has some power to postpone the run once yields have increased. We note, however, that the yield cap may not be targeted directly by the regulator but rather influenced by other policies aimed at the stability of the sponsoring banks. For example, tighter limits to leverage or risk-taking may decrease the bank's borrowing rates and, as a result, they may choose to offer lower maximum yields through their sponsored conduits. Alternatively, regulators may be able to increase the yield cap by lifting the restriction that money-market funds mainly hold A1/P1 rated assets.

We also find that strengthening of the back-up line of credit does not have much power to reduce the run probability once yield spreads reach 27.5 bp. Similarly, at this stage a looser monetary policy that drives down interest rates down will have virtually no impact on the run probability. Once again, our conclusion is that the provision of liquidity to trade the distressed assets has the strongest impact on the probabilities of runs. Moreover, this parameter is still effective even if used late in the build up to the run, provided, of course, that the intervention is not anticipated.

VIII Conclusions

We estimate a dynamic model of debt runs using data from the 2007 crisis in asset-backed commercial paper. The model allows yields to change over time, which introduces dilution risk: the conduit must offer higher yields to induce rollover if conditions worsen, which dilutes the claims of other lenders. Introducing dilution risk to the model can make runs up to 11 times more likely. Our model of fundamental-driven runs fits several features of the data, including the dramatic increase in yields on ABCP leading up to runs, the high probability of recovery once a run starts, the positive relation between yields and the probability of future runs, the overall level of volatility in ABCP yields, and the positive relation between yield volatility and the yield level. We quantify the effect on runs of several policy interventions and find that runs are most sensitive to the conduit's initial

leverage and the expected asset liquidation costs. When high yields signal that a run is imminent, interventions that improve the liquidity of distressed assets are most effective in preventing runs compared to strengthening credit guarantees, reducing the risk-free rate or lifting yields caps.

Our analysis can be extended and improved in two main directions. To keep the estimation tractable, we assume that yields cannot exceed an exogenous cap. We leave open to future research the question of what would be the highest yield the bank would offer before triggering a run. Our conjecture is that the model's predictions would be isomorphic if the sponsor were to track the conduit's residual equity, and either declare default or bring the conduit onto its own balance sheet when residual equity approaches zero.

Second, we have taken the distribution of debt maturities as given. Brunnermeier and Ohmke (2009) propose a simple, two-outcome, two-period model of rollover risk where both the yield spread and maturity of debt adjust in the interim period. In their setup, there is a rat race between creditors to reduce maturities to the shortest possible, i.e., daily. Empirically, we see that the rat race occurs *before* yields adjust: the average maturity drops but then levels off around 25 weeks before runs occur, after which the yields start adjusting upwards. Why maturities and yields adjust sequentially instead of simultaneously is an important question that we also leave for future research.

Appendix 1: Proofs and Derivations

Proof of Proposition 1. Note first that any creditor's continuation payoff must be equal to 1. By definition, for any x_t , the payoffs are

$$\begin{aligned} \max_{\text{run or roll over}} \{1, R_t W(x_t, x^*)\} &= \max_{\text{run or roll over}} \{1, \min[\bar{R}, W(x_t, x^*)^{-1}] W(x_t, x^*)\} \\ &= \max_{\text{run or roll over}} \{1, \min[\bar{R}W(x_t, x^*), 1]\} = 1. \end{aligned}$$

First we show $R_t = \bar{R}$ if $x_t < x^*$. If $x_t < x^*$, creditors will refuse to roll over their loan at maturity. Because running gives them a payoff of 1, rolling over must give them a strictly lower payoff, i.e., $R_t W(x_t, x^*) < 1$. By definition of R_t , this inequality becomes

$$\min[\bar{R}, W(x_t, x^*)^{-1}] \times W(x_t, x^*) < 1.$$

Since $W(x_t, x^*)^{-1} \times W(x_t, x^*) = 1$, it must be that $\min[\bar{R}, W(x_t, x^*)^{-1}] = \bar{R}$. Therefore, $R_t = \bar{R}$.

Suppose that $x_t \geq x^*$. In this case, creditors choose to roll over. If they do so, their payoff must be at least as high as running, which pays 1. Because their payoffs are bounded above by 1, then rolling over must always pay 1. Therefore, for $x_t \geq x^*$

$$\begin{aligned} \min[\bar{R}, W(x_t, x^*)^{-1}] \times W(x_t, x^*) &= 1 \\ \Rightarrow \min[\bar{R}W(x_t, x^*), 1] &= 1. \end{aligned}$$

The previous equality holds if either $\bar{R}W(x_t, x^*) > 1$ for every $x \geq x^*$ or if there exist some $x' \in [x^*, \infty)$ where $\bar{R}W(x', x^*) = 1$ and $\bar{R}W(x_t, x^*) > 1$ for all other $x_t \neq x'$. Because $W(x, x^*)$ is strictly increasing in x , then x' is unique. Moreover, because $\bar{R}W(x', x^*) = 1$ is a minimum, then $x' = x^*$, i.e., the lowest point in the support. In summary, then either

$$R_t = \begin{cases} W(x_t, x^*)^{-1} > \bar{R} & \text{for all } x_t \geq x^*, \\ \bar{R} & \text{if } x_t < x^*. \end{cases} \quad [\text{case (i)}]$$

or

$$R_t = \begin{cases} W(x_t, x^*)^{-1} & \text{if } x_t > x^* \\ \bar{R} & \text{if } x_t = x^* \\ \bar{R} & \text{if } x_t < x^* \end{cases} \quad [\text{case (ii)}].$$

Next we show that case (i) cannot be true, arguing by contradiction. In case (i) we have

$$R^* \equiv W(x^*, x^*)^{-1} < \bar{R}$$

exactly at the run boundary. Hence we have

$$1 = R^* W(x^*, x^*) < \bar{R} W(x^*, x^*). \quad (16)$$

The equality above is from the definition of R^* , and the inequality is from $W > 0$ and $R^* < \bar{R}$. By the assumed continuity of $W(x, x^*)$ at $x = x^*$, there exists a $\xi > 0$ such that for all $x' \in (x^* - \xi, x^*)$, $\bar{R} W(x', x^*) > 1$. We therefore have a contradiction: At $x' < x^*$ the investor runs (since we assume runs happen below x^*), but at x' it is not optimal to run (since $\bar{R} W(x', x^*) > 1$, the payoff from rolling over at $R_t = \bar{R}$, is strictly greater than 1, the payoff from running). ■

Limits of the value function

The numerical procedure below relies on the limit of debt prices W when inverse leverage x becomes large. In this limit, there is effectively no chance of default or runs, so W simplifies to

$$\begin{aligned} \lim_{x \rightarrow \infty} W(x; x^*) &= E_t \left\{ e^{-\rho(\tau-t)} \left[\mathbf{1}_{\{\tau=\tau_\phi\}} + \mathbf{1}_{\{\tau=\tau_\delta\}} \right] \right\} \\ &= \frac{\phi + \delta}{\rho + \phi + \delta}. \end{aligned}$$

Analytical solution to the ODE for $W(x, x^*)$ below the run threshold

Using equations (11) and (12), we can write the general Hamiltonian-Jacobi-Bellman (HJB)

equation:

$$\begin{aligned}
\rho W(x_t; x^*) &= [\mu - \delta(R_t - 1)]x_t W_x(\cdot) + \frac{\sigma^2}{2}x_t^2 W_{xx}(\cdot) \\
&+ \phi[\min(1, x_t) - W(\cdot)] \\
&+ \theta\delta \mathbf{1}_{\{x_t < x^*\}}[\min(1, lx_t) - W(\cdot)] \\
&+ \delta \left[\max_{\text{rollover or run}} \{R_t W(x_t; x^*), 1\} - W(\cdot) \right].
\end{aligned} \tag{17}$$

Since $R_t W(x_t; x^*) \leq 1$, the HJB equation simplifies to

$$\begin{aligned}
\rho W(x_t; x^*) &= [\mu - \delta(R_t - 1)]x_t W_x(\cdot) + \frac{\sigma^2}{2}x_t^2 W_{xx}(\cdot) \\
&+ \phi \min(1, x_t) + \theta\delta \mathbf{1}_{\{x_t < x^*\}} \min(1, lx_t) \\
&- (\phi + \theta\delta \mathbf{1}_{\{x_t < x^*\}} + \delta) W(\cdot) + \delta.
\end{aligned} \tag{18}$$

For a given threshold x^* , the HJB equation can be solved analytically for $x_t < x^* \iff R_t = \bar{R} < W(x_t, x^*)^{-1}$. We rely on this analytical solution in our numerical procedure for finding x^* . The method follows He and Xiong (2011).

When $x < x^*$, the HJB simplifies to

$$\begin{aligned}
0 &= [\mu - \delta(\bar{R} - 1)]x_t W_x + \frac{\sigma^2}{2}x_t^2 W_{xx} \\
&+ \phi \min(1, x_t) + \theta\delta \min(1, lx_t) \\
&- (\rho + \phi + \theta\delta + \delta) W(\cdot) + \delta,
\end{aligned} \tag{19}$$

The exact solution as

$$\begin{aligned}
W(x, x^*) &= d_2 x^\eta + d_3 x^{-\gamma} - \frac{a_5}{a_3} - \frac{a_4}{a_3 + a_1} x, \\
\eta &\equiv \frac{1}{2a_2} \left(a_2 - a_1 + \sqrt{(a_2 - a_1)^2 - 4a_3 a_2} \right) > 0 \\
-\gamma &\equiv \frac{1}{2a_2} \left(a_2 - a_1 - \sqrt{(a_2 - a_1)^2 - 4a_3 a_2} \right) < 0,
\end{aligned}$$

$$\begin{aligned}
a_1 &= (\mu + \delta - \delta \bar{R}) \\
a_2 &= \frac{\sigma^2}{2} > 0 \\
a_3 &= -(\phi + \rho + \theta\delta + \delta) < 0 \\
a_4 &= \theta\delta l \mathbf{1}_{\{x \leq 1/l\}} + \phi \mathbf{1}_{\{x \leq 1\}} \geq 0 \\
a_5 &= \delta + \theta\delta l \mathbf{1}_{\{x \geq 1/l\}} + \phi \mathbf{1}_{\{x \geq 1\}} > 0,
\end{aligned}$$

and coefficients d_2 and d_3 are determined by boundary conditions, value matching, and smooth pasting. Next we examine the cases where $x \leq x^*$ and either $x \leq 1$, $1 \leq x \leq 1/l$, or $x \geq 1/l$. Of course, some of these cases are irrelevant if, for instance, $x^* < 1$.

Case 1: $x \leq 1$

The solution is

$$W(x, x^*) = Ax^\eta - \frac{a_5}{a_3} - \frac{a_4}{a_3 + a_1}x, \text{ for } x \leq 1$$

where

$$\begin{aligned}
a_4 &= \theta\delta l + \phi \\
a_5 &= \delta.
\end{aligned}$$

Following He and Xiong (2011), we eliminate the term with $x^{-\gamma}$ so that the solution does not explode as x approaches zero.

If $x^* < 1$ then we can already solve for A as a function of x^* . Value matching and Proposition 1 imply that

$$\begin{aligned}
W(x^*, x^*) &= A(x^*)^\eta - \frac{a_5}{a_3} - \frac{a_4}{a_3 + a_1}(x^*) = \frac{1}{\bar{R}}, \\
A &= \left[\frac{1}{\bar{R}} + \frac{a_5}{a_3} \right] (x^*)^{-\eta} + \frac{a_4}{a_3 + a_1} (x^*)^{1-\eta}.
\end{aligned}$$

Case 2: $1 \leq x \leq 1/l$

The solution is

$$W(x, x^*) = B_1x^\eta + B_2x^{-\gamma} - \frac{b_5}{a_3} - \frac{b_4}{a_3 + a_1}x$$

where

$$\begin{aligned}
b_4 &= \theta\delta l \\
b_5 &= \delta + \phi \\
B_1 &= A + \frac{\phi}{\gamma + \eta} \left[\frac{\gamma}{a_3} - \frac{\gamma + 1}{a_3 + a_1} \right] \\
B_2 &= \frac{\phi}{\gamma + \eta} \left[\frac{(1 - \eta)}{a_3 + a_1} + \frac{\eta}{a_3} \right] \\
A &= \left(\frac{1}{R} + \frac{b_5}{a_3} \right) (x^*)^{-\eta} + \frac{b_4}{a_3 + a_1} (x^*)^{1-\eta} \\
&\quad - B_2 (x^*)^{-\gamma-\eta} - \frac{\phi}{\gamma + \eta} \left[\frac{\gamma}{a_3} - \frac{\gamma + 1}{a_3 + a_1} \right].
\end{aligned}$$

Case 3: $x > 1/l$

$$W(x, x^*) = C_1 x^\eta + C_2 x^{-\gamma} - \frac{c_5}{a_3} - \frac{c_4}{a_3 + a_1} x,$$

where

$$\begin{aligned}
c_5 &= \delta + \theta\delta l + \phi \\
c_4 &= 0 \\
C_1 &= B_1 + l^\eta \theta \delta \frac{\gamma}{\gamma + \eta} \left[\frac{l}{a_3} - \frac{1}{a_1 + a_3} \left(1 + \frac{1}{\gamma} \right) \right] \\
C_2 &= B_2 + l^{-\gamma} \theta \delta \frac{\eta}{\gamma + \eta} \left[\frac{l}{a_3} - \frac{1}{a_1 + a_3} \left(1 - \frac{1}{\eta} \right) \right].
\end{aligned}$$

Formulas for B_1 and B_2 are above. The expression for A is now

$$\begin{aligned}
A &= \left(\frac{1}{R} + \frac{c_5}{a_3} \right) (x^*)^{-\eta} + \frac{c_4}{a_3 + a_1} (x^*)^{1-\eta} - C_2 (x^*)^{-\gamma-\eta} \\
&\quad - l^\eta \theta \delta \frac{\gamma}{\gamma + \eta} \left[\frac{l}{a_3} - \frac{1}{a_1 + a_3} \left(1 + \frac{1}{\gamma} \right) \right] \\
&\quad - \frac{\phi}{\gamma + \eta} \left[\frac{\gamma}{a_3} - \frac{\gamma + 1}{a_3 + a_1} \right].
\end{aligned}$$

Restrictions on parameter values

We impose the following necessary restrictions on the parameter values. To prevent the firm's fundamental value from exploding or becoming negative, equation (2) requires

$$\mu < \rho + \phi.$$

Second, we limit α , the recovery rate in liquidation, to

$$\alpha < \frac{\rho + \phi - \mu}{\phi}$$

so that $l \equiv \alpha \frac{\phi}{\phi + \rho - \mu} < 1$, i.e., the asset liquidation value $\alpha F(y_t)$ is not enough to pay off all lenders when the firm's maturity value y_t drops below the total book value of outstanding debt, D_t .

Appendix 2: Numerical solution of value function and run threshold

This Appendix describes the algorithm we use to solve numerically for the value function $W(x; x^*)$ and the run threshold x^* . The solution for W satisfies the HJB equation, value matching and smooth pasting for W everywhere (including at $x = x^*$), the limit condition $\lim_{x \rightarrow \infty} W(x, x^*)$, and the condition $W(x^*, x^*) = 1/\bar{R}$. The algorithm follows the following steps:

1. Guess a value for x^* .
2. Solve the HJB for $x \leq x^*$. The analytical solution is in the Appendix above.
3. Solve W numerically for $x > x^*$, as follows:
 - (a) Using the standard method, reduce the order of the ODE by introducing a new variable

Z :

$$W_x \equiv Z \tag{20}$$

$$\begin{aligned} Z_x &= W_{xx} \\ &= -\frac{2[\mu + \delta]}{\sigma^2} \frac{Z}{x} + \frac{2\delta}{\sigma^2} \frac{Z}{xW} - \frac{2\phi \min(1, x)}{\sigma^2 x^2} + \\ &\quad \frac{2(\rho + \phi + \delta)W}{\sigma^2 x^2} - \frac{2\delta}{\sigma^2} \frac{1}{x^2}. \end{aligned} \tag{21}$$

- (b) Solve analytically for $W(x^*; x^*, A(x^*))$ and $W_x(x^*; x^*, A(x^*)) = Z(x^*; x^*, A(x^*))$, using the solutions for W in Appendix 1.
 - (c) Using the initial conditions in step (b), numerically integrate the system of ODEs in step (a) for $x \in [x^*, \bar{x}]$, where \bar{x} is a very large value of x that approximates $x = \infty$.
4. Check whether the numerical solution for $W(\bar{x}, x_*)$ is sufficiently close to its known limit, derived in Appendix 1. If so, we have found the equilibrium threshold x_* . If not, return to step 1.

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Table I: Estimating the Expected Return on ABCP Assets

For each Moody's category with a matched portfolio in Barclays we estimate a time series regression of excess monthly returns on excess returns on three bond risk factors, TERM (long government bonds minus the T-bill rate), DEF_IG (long U.S. corporate investment grade bonds minus long-term government bonds), and DEF_HY (long U.S. corporate high yield bonds minus long-term government bonds). In all cases we use as many months of data as possible. Estimated factor loadings, t-statistics, and R^2 values are in Panel B. Panel A shows the risk premium for each factor, estimated as the average excess return over the longest period of data available. Panel B shows the estimated risk premium for each asset class, estimated as the sum of factor loadings times factor risk premia. All risk premia are in units of fraction per month. Fraction of total CP outstanding is measured on 8/31/2007 and is from Societe Generale. Panel C shows the calculations used to estimate the expected return on ABCP assets.

Panel A: Estimated factor risk premia (fraction per month)						
	TERM	DEF_IG	DEF_HY			
Average	0.27%	0.01%	0.19%			
Standard deviation	2.87%	1.63%	3.82%			
Standard error	0.13%	0.08%	0.21%			
Months used	12/1979 - 12/2010	12/1973 - 12/2010	7/1983 - 12/2010			

Panel B: Estimated factor loadings and risk premia for ABCP asset classes							
Moody's category	Barclay's index	Factor loadings (t statistics)			R^2	Risk premium	Fraction of total CP outstanding
		TERM	DEF_IG	DEF_HY			
Trade receivables	N/A						0.14
Credit cards	US ABS Credit Card	0.33 (9.05)	0.11 (1.65)	0.12 (3.08)	0.32	0.11%	0.12
Auto loans	US ABS Autos	0.18 (8.30)	0.08 (1.84)	0.08 (3.52)	0.32	0.07%	0.11
Securities	US Securitized	0.34 (22.35)	0.03 (1.13)	0.07 (4.48)	0.68	0.10%	0.11
Commercial loans	N/A						0.10
Other mortgages	N/A						0.02
Student loans	US ABS Floating Rate: Student Loans	0.14 (1.85)	-0.02 (-0.16)	0.23 (3.25)	0.38	0.08%	0.07
Residential mortgages	ABX (from Markit)						0.05
Auto leases	US ABS Autos	0.18 (8.30)	0.08 (1.84)	0.08 (3.52)	0.32	0.07%	0.04
CBO & CLO	N/A						0.04
Consumer loans	N/A						0.03
Commercial mortgage loans	US CMBS	0.71 (7.68)	0.10 (0.63)	0.44 (4.70)	0.42	0.28%	0.02
Equipment leases	N/A						0.02
Floorplan	US ABS Autos	0.18 (8.30)	0.08 (1.84)	0.08 (3.52)	0.32	0.07%	0.02
Other mortgages	US MBS	0.32 (20.38)	0.00 (-0.02)	0.05 (3.28)	0.65	0.10%	0.01
Equipment loans	N/A						0.01
Govt guaranteed loans	US Agencies Government Guaranteed	0.54 (19.49)	-0.04 (-0.73)	0.06 (2.23)	0.67	0.16%	0.01
Insurance premiums	N/A						0.01
Others	N/A						0.08

Panel C: Estimation of expected return on ABCP assets (μ)	
Fraction of ABCP with non-missing risk premium	0.520
Weighted average risk premium (per month)	0.098%
Weighted average risk premium (per year)	1.180%
Annualized 1-month T-bill rate on 12/29/2006	4.910%
$\mu = \text{T-bill rate} + \text{risk premium} =$	6.090%

Table II: The Effect of Flexible Prices on Runs

This table compares the predictions from our model, in which yields change over time, to the predictions of He and Xiong (2011), in which yields are constant and set to r . Parameter values are from HX: $\rho = 1.5\%$, $\phi=0.077$, $\alpha = 55\%$, $\sigma = 20\%$, $\mu = 1.5\%$, $y_0 = 1.4$, $\delta = 10$, and $\theta = 5$. Panel A shows the fraction of simulated firms that experience a run in our model within one year, divided by the same fraction from HX. Panel B shows the run threshold in our model (x^*) divided by the run threshold in HX (y^*). Panel C shows the firm's initial market leverage in our model ($= R(x_0; x^*)/y_0$), divided by initial market leverage in HX ($= V(y_0; y^*)/y_0$). \bar{r} is the yield cap in our model.

**Panel A: Ratio of the probability of a run in one year
in our model to He and Xiong (2011)**

	$r = 5\%$	$r = 7\%$	$r = 9\%$
$\bar{r} = 15\%$	1.97	3.89	11.16
$\bar{r} = 20\%$	1.93	3.80	10.87
$\bar{r} = 25\%$	1.90	3.72	10.61

**Panel B: Ratio of the run threshold (assets / debt)
in our model to He and Xiong (2011)**

	$r = 5\%$	$r = 7\%$	$r = 9\%$
$\bar{r} = 15\%$	1.58	1.77	2.00
$\bar{r} = 20\%$	1.57	1.75	1.98
$\bar{r} = 25\%$	1.56	1.74	1.97

**Panel C: Ratio of the initial market leverage (debt / assets)
in our model to He and Xiong (2011)**

	$r = 5\%$	$r = 7\%$	$r = 9\%$
	0.856	0.779	0.706

Table III: Calibration of Conditional Annual Yield Volatilities

This table shows the actual and the model-simulated volatilities rollover yields on asset backed commercial paper across four different bins of the yield levels. All of the known parameters are calibrated to the values in (15). The values of θ , α , and σ are set to 0.78, 0.785 and 0.044, respectively. The rollover yield spread bins result from the partition of yield spreads between 0 and the spread at the run threshold into 5 equally-sized segments.

Yield level bins	Simulated	Yield volatility		95% confidence interval	
		Actual	Standard error	Lower	Upper
1 (Low)	0.134	0.142	(0.004)	0.135	0.149
2	0.203	0.212	(0.005)	0.202	0.222
3	0.227	0.239	(0.006)	0.226	0.251
4 (High)	0.228	0.248	(0.007)	0.233	0.262

Table IV: The Effect of Pre-Crisis Policy Interventions on Runs

This table shows the effect on run probabilities of changing model parameter values, assuming a crisis has not yet started. The first row shows simulated run probabilities using calibrated parameter values. Each following row shows run probabilities using counter-factual parameter values. In each row we change one parameter at a time from its calibrated value to its new value, both shown below. The last column shows the run threshold x^* predicted for the given set of parameter values. Initial yield spreads in these simulations are 15bp. We choose this initial condition so that the simulated probability of a run within one year is 56%, which equals the actual fraction of ABCP programs experiencing runs in 2007.

Policy intervention	Parameters			Probability of a run within τ months			Run threshold (x^*)
	Notation	Base-case value	New value	$\tau = 3$	$\tau = 6$	$\tau = 12$	
None (calibrated values)				0.306	0.453	0.563	1.123
Stronger credit guarantee	Lower θ	0.780	0.680	0.301	0.448	0.559	1.123
More liquidity support	Higher α	0.785	0.805	0.026	0.109	0.224	1.095
Lower risk-free rate	Lower ρ	0.049	0.047	0.310	0.457	0.567	1.124
Higher yield cap	Higher \bar{r}	0.060	0.062	0.291	0.441	0.553	1.123
Shorter debt maturity	Higher δ	9.872	12.175	0.253	0.406	0.525	1.120
Higher expected return	Higher μ	0.061	0.062	0.118	0.254	0.381	1.111
Higher volatility	Higher σ	0.044	0.047	0.349	0.492	0.600	1.124
Longer-horizon conduits	Lower ϕ	0.103	0.093	0.093	0.226	0.354	1.108
Lower initial leverage	Lower $\frac{1}{x_0}$	0.874	0.850	0.019	0.092	0.204	1.123

Table V: The Effect of Within-Crisis Policy Interventions on Runs

This table shows the effect on run probabilities of changing model parameter values, assuming a crisis has already started. The columns in Panel A describe conditions at three different points in time, in order of increasing crisis severity, when policy interventions are implemented. These values provide the initial conditions for the simulations in Panel B. The first row in Panel B shows simulated run probabilities using calibrated parameter values. Each following row shows run probabilities using counter-factual parameter values. In each row we change one parameter at a time from its base-case (i.e. calibrated) value to its new value, both shown below.

Panel A: Policy intervention points						
				(1)	(2)	(3)
				0.275	0.550	0.825
				0.879	0.884	0.888
Panel B: Policy interventions and resulting run probabilities						
Policy intervention	Notation	Parameters		Probability of a run within 3 months		
		Base-case value	New value	(1)	(2)	(3)
None (calibrated values)				0.460	0.683	0.833
Strong credit guarantee	Lower θ	0.780	0.680	0.454	0.676	0.825
More liquidity support	Higher α	0.785	0.805	0.050	0.099	0.142
Lower risk-free rate	Lower ρ	0.049	0.047	0.467	0.690	0.841
Higher yield cap	Higher \bar{r}	0.060	0.062	0.441	0.661	0.807

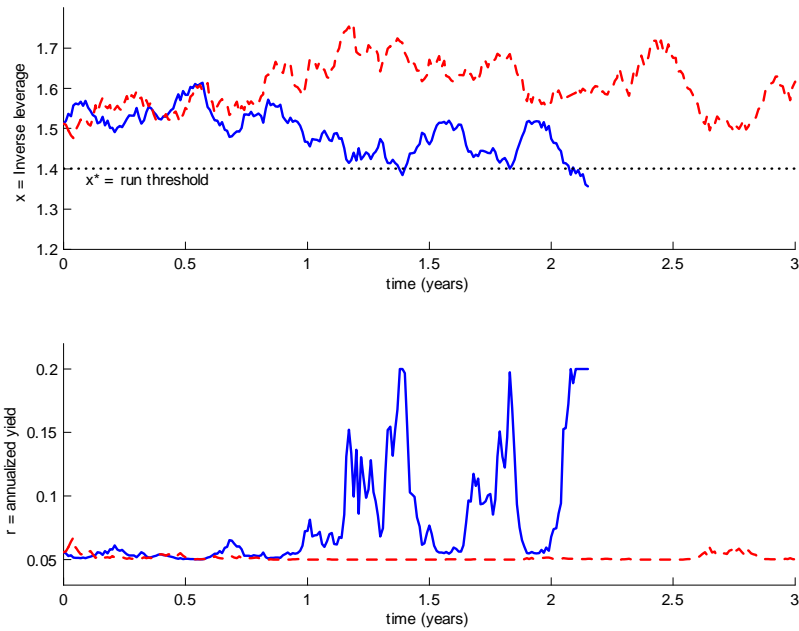


FIGURE 1:

This figure shows two possible simulated paths for a program of a given initial leverage and parameter values. The top panel shows simulated values of x_t , inverse leverage. The dotted black line denotes the run threshold. The bottom panel shows simulated paths of annual yields at rollover for the same two programs. The risk-free rate is 5%, the capped rollover yield is 20%.

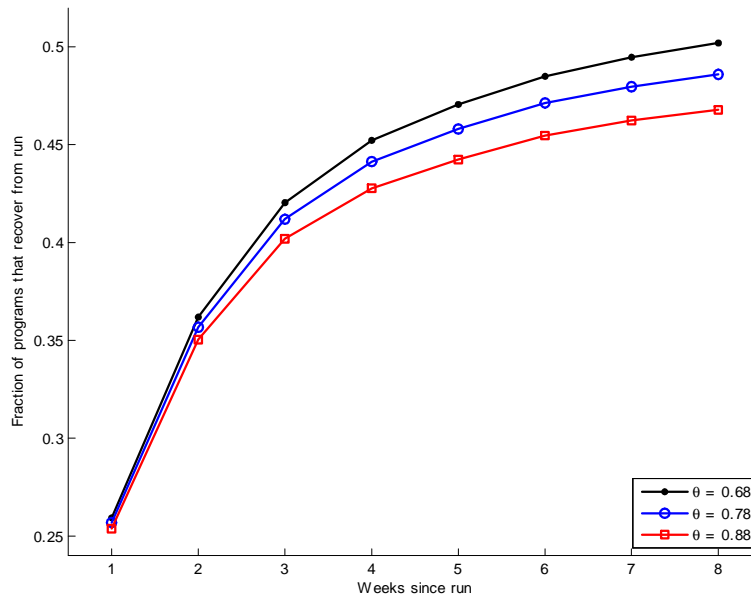


FIGURE 2:

This figure plots the simulated probability of recovery (i.e. issuing paper at least once) within τ weeks of the start of a run. The three lines correspond to three values of θ . Larger values of θ indicate weaker back-up credit lines. The remaining parameters are at their calibrated values in (15).

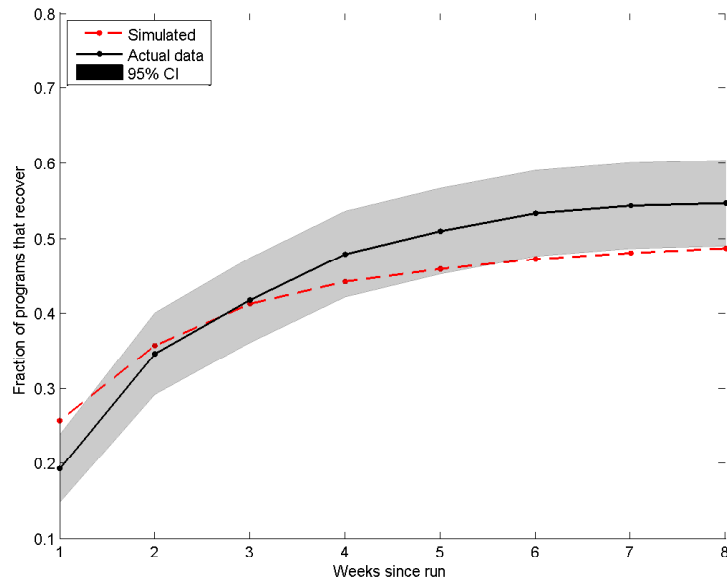


FIGURE 3:

This figure illustrates the calibration of the strength of the credit lines parameter, θ . The black (red) line shows the empirical (simulated) probability that a program recovers from a run (i.e., it reissues commercial paper at least once) within τ weeks of the start of a run. Simulations assume baseline parameter values in (15), and $\theta = 0.78$, $\alpha = 0.785$, and $\sigma = 0.044$.

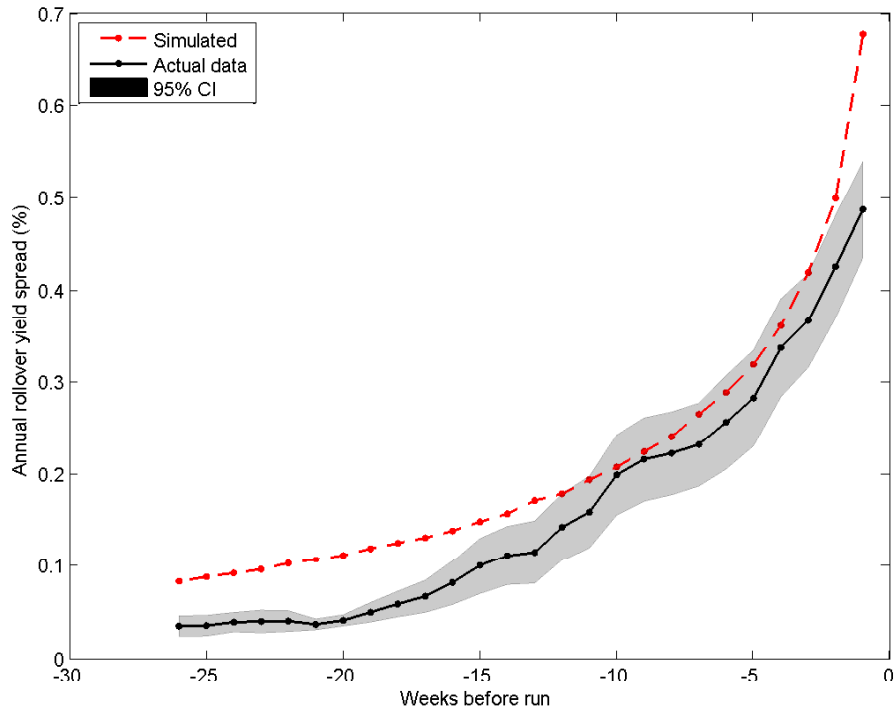


FIGURE 4:

This figure illustrates the calibration of the asset's liquidity, α . The solid black (dashed red) line shows the empirical (simulated) average annualized yield spread in event time before runs. Simulations assume baseline parameter values in (15), and $\theta = 0.78$, $\alpha = 0.785$, and $\sigma = 0.044$.

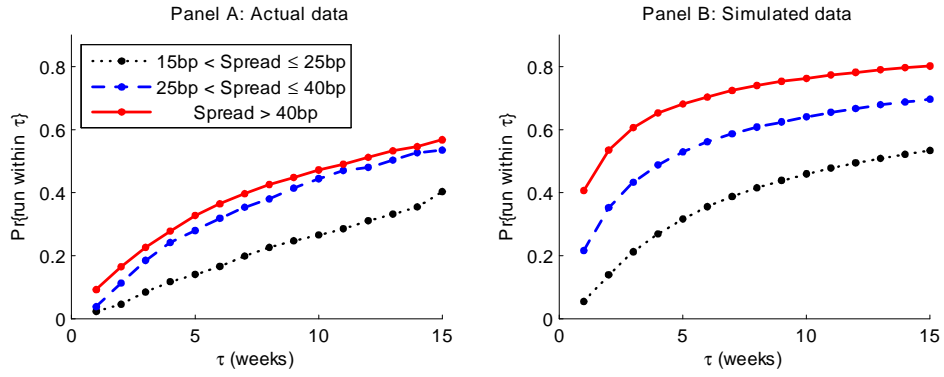


FIGURE 5:

This figure plots the probability of a run within the next τ weeks conditional on the current yield spread. Panel A shows results using actual data. Panel B shows results from data simulated when the parameters are set to the baseline values in (15), $\theta = 0.78$, $\sigma = 0.044$, and $\alpha = 0.785$.

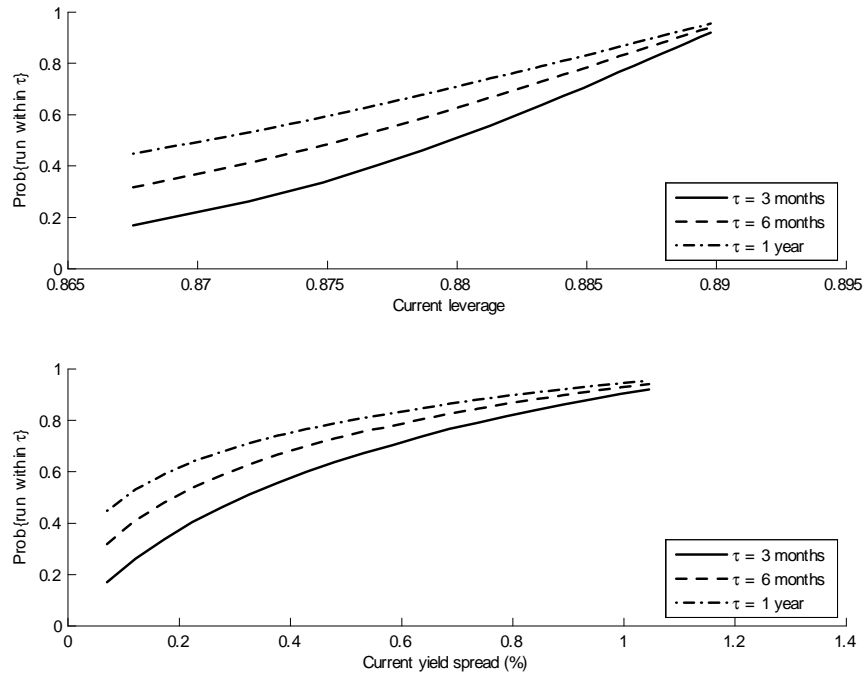


FIGURE 6:

Panel A plots the relation between the firm's current leverage and the probability of a run within the next 3, 6, and 12 months. Panel B shows the relation between the firm's current yield spread and the probability of a future run. Results are from model simulations using the baseline parameter values in (15) and the calibrated values for $\theta = 0.78$, $\alpha = 0.785$, and $\sigma = 0.044$.