Abstract

Purpose – The purpose of this paper is to investigate the phenomena of convergence and stability of leverage reported by Lemmon et al. (2008).

Design/methodology/approach – A dynamic trade-off model of the firm was used to simulate investment, leverage, and payout decisions for different types of firms. From an econometric standpoint, the Efficient Method of Moments was used to recover the structural parameters.

Findings – The structural model generates a leverage ratio that oscillates around a long-run, time-invariant level and consistently reproduces the convergence and stability of leverage reported by Lemmon et al. (2008). The model also suggests the causes of those observed properties of the data. That is, convergence is due to the mean-reversion of profits while stability is due to the different fundamental characteristics (e.g. capital elasticity, volatility of profits, etc.) of the firm.

Practical implications – Determining the optimal capital structure of a firm is a complex problem that has challenged academics and practitioners for a long time. Understanding leverage decisions is of great importance not only for financial managers, but also for investors, such as banks, debt-holders, equity-holders, and other capital providers, who need to understand how firms make capital structure decisions in order to achieve an efficient allocation of funds.

Originality/value – The author shows that the firm-specific fixed effects in leverage regressions are not related to the usual determinants (e.g. profitability, market-to-book ratio), but to the primitive characteristics of the firm (e.g. elasticity of capital in the production function, the volatility of profits, the capital depreciation rate, the income tax rate, etc.)

Keywords Trade-off theory, Dynamic structural model, Efficient method of moments, Firm leverage determinants, Speed of mean-reversion, Structural estimation

Paper type Research paper

I provide further evidence on the determinants of corporate capital structure by estimating a dynamic trade-off model of the firm that includes investment, leverage, and payout decisions. The structural model generates a leverage ratio that oscillates around a long-run, time-invariant level and consistently reproduces the convergence and stability of leverage reported by Lemmon et al. (2008). The dynamic model sheds light on the role played by the primitive characteristics of the firm (e.g. production technology) to explain the cross-sectional variation in capital structure. I use Efficient Method of Moments (EMM) to recover the structural parameters.

The question about the determinants of leverage is central in corporate finance, but researchers have not yet reached a consensus about it. Several studies (e.g. Titman and Wessels, 1988; Rajan and Zingales, 1995; Frank and Goyal, 2009, and many others) report different time-dependent firm characteristics that partially explain the variation in firm leverage. Lemmon et al. (2008) show that, even after introducing all those determinants, most of the heterogeneity in capital structure is explained by

JEL Classification — G32, G35
firm-specific fixed effects. That is, they find that whereas traditional determinants help to understand the evolution of leverage over time, most of the variation in capital structure across firms is captured by firm-specific fixed effects. I derive a dynamic model of the firm to study leverage decisions and show that it produces results consistent with those of the latter. My structural model allows me to explain the primitive firm characteristics underlying the aforementioned fixed effects.

The dynamic model in the present paper is based on the trade-off theory of capital structure and, therefore, explicitly captures the effect of leverage on firm value introducing the benefits (i.e. interest tax shields) and costs (i.e. costs of financial distress) of debt. The model produces leverage ratios that fluctuate around a long-run, time-invariant level as the firm receives different profit shocks over time, as reported by Flannery and Rangan (2006). This mean-reversion of leverage is due to both the active management of the debt-equity ratio by the firm and the mean-reversion of profit shocks.

I use the model to construct a panel of different types of firms and show it generates the leverage patterns found by Lemmon et al. (2008). Being structural, my approach allows me to shed light on certain determinants of firm leverage that are not captured by the latter. First, I reproduce their leverage regressions and find that the dynamic model consistently replicates their results. The power of traditional determinants of capital structure, mainly profitability and market-to-book ratio, to explain leverage decisions turns out to be fairly small, while most of the variation in leverage across firms is explained by the fixed effects around which leverage oscillates for each type of firm in the panel. The structural approach I follow allows me to explain the key determinants of those fixed effects. Via a sensitivity analysis, I show that, in my model, these values are determined by the primitive characteristics of the firm, such as the volatility of profits, the elasticity of capital, the rate of depreciation of capital, and the income tax rate.

Second, I investigate the patterns of convergence and stability of leverage reported by Lemmon et al. (2008). I show that these observed properties of the data appear in the context of my dynamic model and provide a simple explanation for them. By using the simulated panel, I construct both the actual and “unexpected” leverage portfolios and find that the dynamic model replicates their results very closely. In the context of the dynamic model, convergence of leverage is generated by the fact that firm leverage decisions are mean-reverting. Thus, when averaged into the four portfolios, firms with relatively high (low) leverage tend to return to more moderate levels of leverage over time. Leverage stability refers to the observation that firms with relatively high (low) leverage tend to keep relatively high (low) leverage for long periods of time. This feature of the data appears in the context of the dynamic model because the leverage ratio of each firm type in the panel mean-reverts to a different constant value. Consequently, the long-run values to which the four portfolios converge are the average of the unconditional means of leverage decisions of all firms included in the corresponding portfolio. As before, these results suggest that the firm-specific fixed effects explain most of the cross-sectional variation in leverage, and the power of the usual time-varying determinants to explain such variation is fairly limited. In the context of my model, those fixed effects are determined by the fundamental characteristics of the firm I described in the previous paragraph.

Finally, I use the previous panel to study the mean-reverting properties of leverage decisions. In particular, the speed of mean-reversion of leverage is still subject to great debate in the literature[1]. I find that leverage mean-reverts to the long-run constant level at a moderate speed of 35.87 percent per year. This estimate is close to the
empirical evidence of Flannery and Rangan (2006) and DeAngelo et al. (2011), who suggest speeds of adjustment of 34.40 and 37.80 percent per year, respectively.

From an econometric standpoint, to the best of my knowledge, this is the first paper in corporate finance that uses the EMM developed by Gallant and Tauchen (1996) to estimate the model parameters. EMM is a systematic approach for selecting moments when estimating a structural model using Generalized Method of Moments (i.e. the researcher does not need to choose arbitrary moments). The key idea of this approach is to match the moments implied by the structural model to the moments implied by the data.

EMM estimation can be regarded as a two-stage procedure. In the first stage, I use a semi-nonparametric (SNP) density function to describe the statistical properties of the data, namely, investment and leverage decisions. The outcome of this stage is a family of density functions for the joint distribution of the data, and I choose the one that best fits the sample in the most parsimonious way. I recover the structural parameters of the dynamic model in the second stage. These estimators are those that generate simulations of investment and leverage decisions as close as possible to the observed data. The estimates of the structural parameters are consistent with the findings in the previous literature, have the correct sign according to economic theory, and are statistically significant.

Overall, determining the optimal capital structure of a firm is a complex problem that has challenged academics and practitioners for a long time. Understanding leverage decisions is of great importance not only for financial managers, but also for investors, such as banks, debt-holders, equity-holders, and other capital providers, who need to understand how firms make capital structure decisions in order to achieve an efficient allocation of funds. From a practical perspective, the results in this paper suggest that the fundamental characteristics of the firm (i.e. elasticity of capital, capital depreciation rate, etc.) could be used by practitioners to infer the firm's optimal leverage, as well as its evolution over time. For instance, a bank analyzing a potential loan to a firm could estimate whether the firm still has debt capacity, depending on its current debt and the optimal leverage inferred from its primitive features. Furthermore, the finding that the debt ratio is mean-reverting could be used by the bank to predict the firm's likely evolution of leverage in the future.

I. Literature review
Leverage decisions have been analyzed extensively in the corporate finance literature. For example, Titman and Wessels (1988) find that leverage is significantly related to firm size, profitability, and the uniqueness of the firm’s line of business. Using international data, Rajan and Zingales (1995) report that the factors that are significant leverage determinants for US firms (e.g. profitability, market-to-book ratio, sales, etc.) are similarly important in other developed countries. In a more recent study, Frank and Goyal (2009) find that profitability, market-to-book ratio, and firm size, among others, are the most reliable factors explaining capital structure decisions. However, Lemmon et al. (2008) challenge that literature suggesting that the explanatory power of those determinants is rather limited and that most of the variation in capital structure at the cross-sectional level is captured by firm-specific fixed effects, which proxy for unobserved factors. This study complements the latter by using a dynamic model of the firm to both confirm their results and provide some insights on the possible factors underlying the unobserved fixed effects.

From the methodological perspective, this paper is closest to Hennessy and Whited (2007), who use a dynamic model of the firm to estimate the magnitude of the costs of
external financing. Hennessy and Whited (2005) also use a dynamic model to explain empirical findings apparently inconsistent with the static trade-off theory. My analysis complements those studies by both focussing on the structural causes of the unobserved heterogeneity described by Lemmon et al. (2008) and using EMM to estimate the structural parameters.

The paper is organized as follows. Section II describes the model. In Section III, I describe the data used for estimation. I discuss the identification strategy in Section IV. In Section V, I examine the EMM procedure and present the estimation results. Section VI analyzes the predictions of the model about leverage decisions and presents the main results of the paper. Section VII concludes.

II. The model

The methodology I use to develop the model is discrete time, infinite horizon, stochastic dynamic programming. The objective of the firm is to maximize its value, which is achieved by maximizing the expected discounted sum of cash flows to investors.

Agents are risk-neutral and use the risk-free rate of interest, \( r_f \), as their discount rate. State variables with primes indicate values in the next period, e.g., next-period profits are referred as \( z' \), while state variables with minus signs indicate values in the previous period, e.g., previous-period profits are \( z^- \). Finally, current values of state variables are indicated with no sign, e.g., current-period profits are \( z \).

There are two endogenous state variables: capital \( k \) and debt \( d \). The capital of the firm, \( k \), is used for production and can vary (i.e. increase or decrease) over time because of investment decisions and depreciation. In each period, capital depreciates at a constant rate \( \delta \).

The debt of the firm, \( d \), matures in one period and is rolled over every period. The total amount of debt can be increased or decreased over time according to the debt decisions. The debt contract includes a positive net worth covenant by which if, in any period, the value of the firm falls below the nominal value of the debt, the firm goes into bankruptcy and is liquidated. Therefore, the bond yield required by debt-holders will depend on the probability of bankruptcy (described in detail below.)

There is one source of uncertainty that drives the optimal policies of the firm, the profitability shock, \( z \). This shock changes the marginal profitability of capital, making it more or less attractive to invest. Therefore, high realizations of \( z \) are followed by large investment decisions, and vice versa. I assume state variable \( z \) follows an AR(1) process:

\[
    z' = c + \rho_z z + \epsilon'
\]  

where \( 0 < \rho_z < 1 \) and \( \epsilon \) is an iid truncated normal random variable with mean 0 and variance \( \sigma^2_z \). Therefore, if \( \epsilon \) takes values in the compact set \( E = [\underline{z}, \bar{z}] \), then shock \( z \) takes values in the compact set \( Z = [\underline{z}, \bar{z}] \) with \( \underline{z} = c + \bar{z} / (1 - \rho_z) \) and \( \bar{z} = c + \bar{z} / (1 - \rho_z) \).

The operating profits of the firm, \( \pi(k, z) \), depend on the capital in place, \( k \), and the profitability shock, \( z \), in the following way:

\[
    \pi(k, z) = zk^\alpha
\]  

where \( \alpha \in (0, 1) \). Equation (2) shows that the operating profit function is of the Cobb-Douglas form with decreasing marginal profitability.

I assume issuing debt and equity is costly. This assumption incorporates the direct evidence provided by Altinkilic and Hansen (2000) on the importance of underwriter fees. Furthermore, they suggest that the costs of issuance are convex,
both for debt and equity. Consequently, I assume the external finance cost function is linear-quadratic:

\[ c_i(x^d, x^e) = \phi_d \left[ \lambda_1^d x^d + \lambda_2^d \frac{(x^d)^2}{d} \right] + \phi_e \left[ \lambda_1^e x^e + \lambda_2^e \frac{(x^e)^2}{k-d} \right] \tag{3} \]

where \( x^d \) and \( x^e \) are the two decision variables. The former refers to debt reductions (-) and increments (+) while the latter refers to equity payouts (-) and issuances (+). Parameters \( \lambda_1^d \) and \( \lambda_2^d \) reflect the costs of issuing debt, while parameters \( \lambda_1^e \) and \( \lambda_2^e \) reflect the costs of issuing equity. The indicator function \( \phi_d \) equals 1 if \( x^d > 0 \), and 0 otherwise. Similarly, the indicator function \( \phi_e \) equals 1 if \( x^e > 0 \), and 0 otherwise. This means that issuing capital is costly while reducing it is not.

Corporate earnings are taxed at rate \( \tau_c \). Therefore, the firm’s net income is defined by:

\[ NI = \left[ \pi(k, z) - \delta k - c_i(x^d, x^e) - r_d(k, d, k^-, d^-, z^-)d \right] (1 - \tau_c) \tag{4} \]

where \( r_d(k, d, k^-, d^-, z^-) \) is the bond yield required by debt-holders during the last period (described in detail below.)

Finally, the internal cash flow of the firm is:

\[ ICF = \left[ \pi(k, z) - \delta k - c_i(x^d, x^e) - r_d(k, d, k^-, d^-, z^-)d \right] (1 - \tau_c) + \delta k \tag{5} \]

and its utility in each period, or cash flow to investors, is:

\[ u(k, d, z, k^-, d^-, z^-, x^d, x^e) = -x^d + r_d(k, d, k^-, d^-, z^-)d - x^e. \tag{6} \]

This is the cash flow received (+) or provided (-) by firm investors in each period.

I now define the transition functions and state space of the two endogenous state variables. The state equation of capital \( k \) satisfies the accounting cash-flow equation and is defined as:

\[ k' = k(1 - \delta) + ICF + x^d + x^e. \tag{7} \]

Equation (7) means that, every period, the firm invests an amount equal to \( ICF + x^d + x^e \). The capital, \( k \), of the firm takes values in the compact set \( K = [0, \bar{k}] \) where \( \bar{k} \) is the maximum level of capital. Following Gomes (2001) and Hennessy and Whited (2005, 2007), I assume that under the highest profitability shock, \( \bar{z} \), capital \( \bar{k} \) satisfies:

\[ \pi(\bar{k}, \bar{z})(1 - \tau_c) - (\delta + r_f)\bar{k} = 0. \tag{8} \]

Intuitively, at capital level \( \bar{k} \), after-tax operating profits just cover depreciation and the opportunity cost of capital. Therefore, it is not economically profitable to accumulate capital to a level \( k > \bar{k} \).

The transition function of debt \( d \) is defined as:

\[ d' = d + x^d. \tag{9} \]

The variable \( d \) takes values in the compact set \( D = [0, \bar{k}] \).
The previous restrictions on the state space of \( k \) and \( d \) bind the decision variables \( x^d \) and \( x^e \) to a compact set. Specifically:

\[
x^d \in \left[-d, \bar{k} - d\right] \quad \text{and} \quad x^e \in \left[-(k-d), \bar{k} - (k-d)\right].
\] (10)

As stated above, the objective of the firm is to maximize its value, which is achieved by maximizing the expected discounted sum of cash flows to investors. Therefore, the maximization problem faced by the firm is:

\[
v_0 = \sup_{x^d_t, x^e_t} E_{t=0}^{\infty} \frac{1}{(1+r_f)} y_t \quad \text{subject to} \quad d_t < k_t
\] (11)

where \( v_0 \) is the current value of the firm, \( E \) is the expectation given current information (i.e. initial capital stock, debt and profitability shock), and \( y_t \) is defined as:

\[
y_t = u \left( k_t, d_t, z_t, k_{t-1}, d_{t-1}, z_{t-1}, x^d_t, x^e_t \right) \quad \text{if} \quad v_t > d_t
\]
\[
y_t = L_t, y_{t+1} = y_{t+2} = \ldots = 0 \quad \text{if} \quad v_t \leq d_t
\] (12)

where \( L_t \) is the liquidation value of the firm at moment \( t \) as described below by Equation (13). The interpretation of the maximization problem is as follows: every period the firm must choose \( x^d_t \) and \( x^e_t \) in such a way that it maximizes the expected discounted sum of cash flows to investors (this refers to the first line of Equation (12)). However, if in any period the value of the firm falls below the nominal value of the debt, it goes into bankruptcy while investors receive its liquidation value and zero thereafter (this refers to the second line of Equation (12)).

The model assumes the debt is protected with a positive net worth covenant, and thus the bankruptcy-triggering event consists in the value of the firm falling below the nominal value of the debt. In that case, the firm goes into bankruptcy and is liquidated. Accordingly, the (liquidation) value of the firm that goes into bankruptcy is:

\[
v(k, d, z, k^-, d^-, z^-) = L = [k(1-\delta) + ICF_b] (1-\bar{\xi})
\] (13)

where \( ICF_b = [\pi(k, z) - \delta k](1-\tau_r) + \delta k \) is the internal cash flow in the period previous to bankruptcy and \( \bar{\xi} \) reflects the direct costs of bankruptcy. Intuitively, the liquidation value of the firm is the realization into cash of total assets (depreciated capital plus internal cash flow) minus the direct costs of bankruptcy.

In the event of bankruptcy, the recovery amount accruing to debt claimants is:

\[
R(k, d, z) = \min \{ L, d \} = \min \{ [k(1-\delta) + ICF_b] (1-\bar{\xi}), d \}.
\] (14)

Equation (14) means that the value accruing to debt-holders is the minimum between the liquidation value of the firm and the nominal value of the debt. Accordingly, fair pricing of debt requires the fulfillment of the following equation:

\[
d' = \frac{1}{1+r_f} \left[ (1-\phi_b) d' (1+r_d) + \phi_b R(k', d', z') \right] F(d' | k, d, z)
\] (15)

where the indicator function \( \phi_b \) equals 1 if the firm goes into bankruptcy, and 0 otherwise. This equation means that debt-holders require a bond yield, \( r_d \), which equates the nominal value of the debt (left-hand side) to the expected discounted payoff of debt in the next period (right-hand side). If the firm avoids bankruptcy, the debt
payoff is the nominal value plus the promised yield, \(d'(1+r_d)\). On the contrary, if the firm does go into bankruptcy, the debt payoff is the recovery amount, \(R(k', d', z')\).

Furthermore, the bond yield required by debt claimants can be solved for explicitly and is given by:

\[
\frac{1}{1+r_f}F(d' | k, d, z) - 1.
\]

The last step to complete the dynamic model of the firm is to describe its recursive formulation. Let \(v = v(k, d, z)\). Then, the value of the firm that does not go into bankruptcy is given by the following Bellman equation:

\[
v = \sup_{x, s} \left\{ u(k, d, z, k^{-}, d^{-}, x^{-}, x') + \frac{1}{1+r_f} \int \left[ (1-\phi_b) v' + \phi_b L \right] F(d' | k, d, z) \right\}
\]

subject to \(d' < k'\).

This value function represents the maximized value of the firm, namely, the maximized expected discounted sum of cash flows to investors.

The implementation of the model is described in the Appendix. Finally, let \(\beta = 1/(1+r_f)\), then the complete vector of model parameters is \((\beta, \delta, c, \rho, \sigma, \lambda, \lambda')\).

### III. Data

The data used in this study are from the yearly Standard & Poor’s Compustat industrial files. The sample includes all firms in the database and covers the period 1988-2009. To select the sample, I follow a procedure similar to that of Hennessy and Whited (2007). I delete firm-year observations with missing or negative data. Furthermore, I include in the sample only firms that have at least two consecutive years of data. Finally, I exclude regulated, financial or public service firms, that is, I exclude all firms whose primary SIC code is between 4,900 and 4,999, between 6,000 and 6,999, or greater than 9,000. After this procedure, the final sample includes 14,465 different firms and 111,944 firm-year observations.

Data variables are defined in the following way: capital \(k\) is Book Assets – Total and debt \(d\) is Long-Term Debt – Total plus Debt in Current Liabilities – Total. For estimation purposes, I compute the following two decision variables: investment ratio, \(i\), and book leverage, \(l\). Therefore, these decision variables are computed as:

\[
i = \frac{k' - h(1-\delta)}{k(h(1-\delta))}
\]

\[
l = \frac{d}{k'}
\]

Table I shows summary statistics of the sample. I eliminate observations with investment > 200 percent to reduce the effect of extreme observations and eradicate errors in the data[3]. Consistently with previous empirical evidence, the investment ratio decision has a mean value of 11.58 percent per year, while the book leverage decision has a mean value of 46.55 percent.
IV. Identification
I discuss the sources of identification of \( \rho = (\delta, c, \rho_z, \sigma, \alpha, \lambda_1^d, \lambda_2^d, \lambda_1^e, \lambda_2^e, \xi) \), the vector of structural parameters of the model that will be estimated. To achieve identification of these ten model parameters, I assume the remaining two parameters have the following values: \( \beta = 0.98, \tau_c = 35 \) percent. The value of \( \beta \) implies a risk-free rate of interest, \( r_f \), of 2.04 percent per year. I fix the value of the tax rate, \( \tau_c \), because it was relatively constant during the period 1988-2009.

Firm decisions are simultaneous and interrelated, and all model parameters will have some impact on them. However, I can use certain data moments to identify model parameters. The mean of investment is informative about the capital depreciation rate, \( \delta \). A larger depreciation rate should imply more investment on average. Variability of firm investment is informative about the concavity of the profit function parameter, \( \alpha \). The lower the parameter, the lower the marginal profitability of the firm, which means that firm investment should respond less aggressively to profitability shocks.

The relative size of debt and equity issuances helps me identify the cost of issuing debt, \( \lambda_1^d \) and \( \lambda_2^d \), and the cost of issuing equity, \( \lambda_1^e \) and \( \lambda_2^e \). Larger costs of issuing debt compared to equity should induce relatively larger issuances of equity, and vice versa. The variability of debt and equity issuances also helps me to pin down parameters \( \lambda_2^d \) and \( \lambda_2^e \). The lower the quadratic parameters, the less convex the cost of external capital function of the firm, which means that debt and equity issuances should be larger for a given profitability shock. The average level of firm leverage is informative of the direct costs of bankruptcy, \( \xi \). Higher average levels of leverage imply lower direct costs of bankruptcy. Finally, because leverage is a relatively linear function of the profit shock, I can use the variation of leverage decisions (e.g. its persistence and variability) plus the parametric assumptions about the profitability shock (i.e. state variable \( z \) follows an AR(1) process) to identify the remaining three parameters of the process, \( c, \rho_z, \) and \( \sigma_e \).

V. Estimation
This section presents the estimates of the structural parameters of the dynamic model. The estimation technique I use is the EMM developed by Gallant and Tauchen (1996). The underlying idea of the methodology is to match the moments generated by the simulation of the model to those implied by the observed data.

EMM estimation consists of two steps. In the first step, I characterize the statistical properties of the data and select the density function that best fits the sample. In the second step, I recover the structural parameters of the dynamic model.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>Skewness</th>
<th>Kurtosis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Investment ratio</td>
<td>0.1158</td>
<td>0.0563</td>
<td>0.3687</td>
<td>-0.9977</td>
<td>1.9998</td>
<td>1.6105</td>
<td>8.0830</td>
</tr>
<tr>
<td>Book leverage</td>
<td>0.4655</td>
<td>0.4707</td>
<td>0.2301</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.0629</td>
<td>2.2226</td>
</tr>
<tr>
<td>No. observations</td>
<td>109,049</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** The sample consists of all firms in the Compustat database from 1988 to 2009, except regulated, financial or public service firms. The table presents the mean, median, standard deviation, minimum and maximum values, skewness, and kurtosis of investment and leverage in the final sample. Investment ratio is \( [k' - k(1 - \delta)]/k(1 - \delta) \), while book leverage is \( d'/k' \).
A. Description of the statistical properties of the data
I use the SNP density function, as proposed by Gallant and Tauchen (1989), to describe the statistical features of the data (i.e. investment and leverage decisions). The SNP density is a general-purpose model with which I generate a family of density functions for the joint distribution of the data. I then select the density function that best characterizes the data in the most parsimonious way.

I find that the SNP density function that best fits the sample of investment and leverage decisions is a bivariate normal density function with a VAR(1) structure for the mean and an ARCH(3) structure for the variance. The description of the construction of the SNP density function for the present study is available on my webpage[4].

B. Estimation of structural parameters
The objective of this second step is to estimate the vector of parameters of the dynamic model, \( \rho = (\delta, c, \rho_z, \sigma, \alpha, \lambda^d_1, \lambda^d_2, \lambda^c_1, \lambda^c_2, \xi) \). From the previous step, I have the SNP density that best characterizes the data. The score function of this density is used to construct the vector of moments that will be used in the GMM objective function. For a candidate set of parameter values, I simulate the model and compute the objective function. Then, by using a non-linear optimizer, I search for the parameter values that minimize the GMM criterion.

After simulating the decisions of the firm, the moment equations are computed as:

\[
m(\rho, \tilde{\theta}_n) = \frac{1}{N} \sum_{t=1}^{N} \frac{\partial}{\partial \theta} \log f(\tilde{y}_t | \tilde{x}_{t-1}, \tilde{\theta}_n) \]  

(19)

where \( (\tilde{y}_t)^N_{t=1} \) are the simulated data, \( N \) is the length of the simulation, and \( \tilde{\theta}_n \) is the quasi-maximum likelihood estimate of the parameter vector, \( \theta \), of the SNP density function selected in the first step.

The EMM estimator is:

\[
\hat{\rho}_n = \arg\min_{\rho} m(\rho, \tilde{\theta}_n) \left( I_n \right)^{-1} m(\rho, \tilde{\theta}_n) \tag{20}
\]

with \( I_n = \frac{1}{n} \sum_{t=1}^{n} \left[ \frac{\partial}{\partial \theta} \log f(y_t | x_{t-1}, \tilde{\theta}_n) \right] \left[ \frac{\partial}{\partial \theta} \log f(y_t | x_{t-1}, \tilde{\theta}_n) \right]^\prime \), where the weighting matrix \( I_n \) assumes the SNP density function closely approximates the true stochastic process of \( y_t \).

Under standard regularity conditions, the EMM estimator is consistent and asymptotically normal. If the SNP density closely approximates the true data generating process, then the efficiency of the EMM estimator will be close to that of maximum likelihood.

For each possible set of parameter values, the simulation length is 100,000 periods after discarding the first 200 periods to avoid the influence of starting values. As before, I assume \( \beta = 0.98 \) and \( \tau_c = 35 \) percent. Therefore, the vector of model parameters to estimate is \( \rho = (\delta, c, \rho_z, \sigma, \alpha, \lambda^d_1, \lambda^d_2, \lambda^c_1, \lambda^c_2, \xi) \). Table II exhibits EMM point estimates of model parameters, standard errors and \( p \)-values. All estimated parameters are statistically significant, as suggested by the small \( p \)-values.

The estimate of the depreciation parameter, \( \delta \), at 0.073 per year is a reasonable value considering that the mean investment ratio, shown in Table I, is 0.116 per year. The estimate of the persistence parameter of the profitability shock process, \( \rho_z \), is 0.672.
This value is similar to that reported by Hennessy and Whited (2007). The estimated value for the conditional standard deviation of the profitability shock, \( \sigma_e \), is 0.391, which is slightly above the value estimated by DeAngelo et al. (2011). I find parameter \( c \) to be 0.527, which implies that the unconditional mean of profitability shock is positive (given that \( \rho_z \) is also positive).

The estimate of the parameter related to the concavity of the profit function, \( \alpha \), is 0.624 – consistent with the value found by Cooper and Haltiwanger (2006), Hennessy and Whited (2007), and DeAngelo et al. (2011). Debt cost parameters \( \lambda_1^d \) and \( \lambda_2^d \) are estimated at 0.009 and 0.0004, respectively, while equity cost parameters \( \lambda_1^e \) and \( \lambda_2^e \) estimated at 0.095 and 0.005, respectively. These values are close to those reported by Altinkilic and Hansen (2000), Hennessy and Whited (2007), and DeAngelo et al. (2011). Finally, the estimated value of the direct costs of bankruptcy parameter, \( \xi \), is 0.141, which is slightly above that reported by Hennessy and Whited (2007).

VI. Model predictions about capital structure choice

The identification of the determinants of capital structure is a strongly contested area in corporate finance. Part of the literature (e.g. Titman and Wessels (1988); Rajan and Zingales (1995); Frank and Goyal (2009), etc.) suggests that variation in capital structure is explained by time-varying firm characteristics, such as profitability and growth opportunities. On the other hand, Lemmon et al. (2008) suggest that the role of those factors in the determination of leverage is fairly limited and, therefore, important factors are missing in existing regressions. I use the dynamic model to investigate these issues in the following subsections. In agreement with the latter, I find that most of the variation in leverage is explained by the fundamental characteristics of the firm and the power of traditional determinants to explain such variation is rather small.

A. Features of the model

In every period, the firm maximizes its value by choosing optimal capital and leverage depending on the current state of the model. The result of this behavior is shown in
Figure 1, which displays leverage decisions made by a single firm over time as it receives random profit shocks. The firm is simulated at the base case parameters over 1,000 periods (after removing the first 200 observations to eliminate the influence of an arbitrary starting point.) Although optimal leverage changes over time, this type of dynamic models has a constant target leverage in the long-run sense, concept that is described in DeAngelo et al. (2011). The target capital structure is the leverage ratio to which the firm would converge if it were to receive the same neutral profit shock for a long time (i.e. many periods in a row). Figure 1 also shows target leverage of the firm for the current model. After period 700, I make the firm receive a neutral profit shock ($z = c$) for a long time and optimal leverage converges to the long-run constant target.

I also study whether leverage is mean-reverting, that is, whether leverage oscillates around a long-run mean level. As before, I simulate a single firm at the values of the parameters estimated in Section V. A standard autoregressive model of book leverage is:

$$\frac{d_{t+1}}{k_{t+1}} = a_1 b_{ML} + (1-a_1) \frac{d_t}{k_t} + \epsilon_{t+1}$$ (21)

where $d_{t+1}/k_{t+1}$ is book leverage, $b_{ML}$ is the long-run mean book leverage, and $a_1$ can be interpreted as the speed of mean-reversion. The estimates suggest that firm leverage is, indeed, mean-reverting to the long-run constant value. The coefficient $a_1$ is 0.3350. This estimate implies a moderate speed of adjustment of 33.50 percent per year. This estimated speed of mean-reversion is close to that found by Flannery and Rangan (2006).
who suggest a speed of adjustment of 34.40 percent per year. DeAngelo et al. (2011) also report a similar speed of adjustment of 37.80 percent per year.

To summarize, in the context of the dynamic model the firm maximizes its value every period after receiving a profit shock by changing its size and rebalancing its capital structure. This implies that active management of leverage ratios coupled with a mean-reverting profit shock induces the observed mean-reversion of leverage.

B. Structural differences versus traditional determinants

Lemmon et al. (2008) suggest that traditional determinants of leverage, such as profitability and market-to-book ratio, have limited power to explain the observed variation in leverage. I use the dynamic model to create a panel of firms and study these features of leverage behavior. The panel is composed of 100 firms and firm decisions are simulated using the parameter values estimated in Section V. This sample is divided into ten types or groups of ten identical firms, and each type is different in parameter $\sigma$, that is, they differ with respect to the volatility of profit shocks that firms in each group face (parameter $\sigma$ ranges from 0.1 to 0.7). This source of heterogeneity introduces variation in all firm decisions and, in particular, in the unconditional mean of leverage decisions for each type of firm. That is, because each type of firm in the panel is simulated under different primitive assumptions (i.e. different volatility of profit shocks), leverage decisions of each firm type fluctuates around a different mean value. I obtain analogous results if I introduce heterogeneity across groups using the other model parameters, such as the capital elasticity ($\alpha$), the depreciation rate ($\delta$), etc.

Each of the 100 firms is simulated over 1,000 periods after discarding the first 200 observations to eliminate the influence of an arbitrary initial point.

First, I investigate the role of firm’s initial leverage in the determination of future leverage. Accordingly, I estimate the following regression:

$$
\frac{d_{i,t+1}}{k_{i,t+1}} = b_0 + b_1 \frac{d_{i,0}}{k_{i,0}} + b_2 \frac{\pi(k_{i,t}, z_{i,t})}{k_{i,t}} + b_3 \frac{v_{i,t}}{k_{i,t}} + b_4 \sigma_{n_{i,t}} + b_5 \frac{div_{i,t}}{k_{i,t}} + e_{i,t+1}
$$

where $d_{i,t+1}/k_{i,t+1}$ is book leverage, $d_{i,0}/k_{i,0}$ is initial book leverage, $\pi(k_{i,t}, z_{i,t})/k_{i,t}$ is profitability (operating profits), $v_{i,t}/k_{i,t}$ is the market-to-book ratio (investment opportunities), $\sigma_{n_{i,t}}$ is the volatility of operating income, and $div_{i,t}/k_{i,t}$ is lagged dividends. Index $i$ refers to firm $i$, while index $t$ refers to time period $t$.

Table III shows the results from estimating different specifications of Equation (22). Column (1) shows the coefficients corresponding to the regression of leverage on its usual determinants (e.g. profitability, market-to-book ratio, operating income volatility, and lagged dividends) excluding initial leverage. The adjusted $R^2$ of this specification is a modest 10 percent. Initial leverage alone, as shown in column (2), accounts for 35 percent of the variation in book leverage, which suggests that an important part of the variation in capital structure is due to stable factors. Column (3) presents the results from estimating Equation (22) (i.e. including initial leverage), which shows that the adjusted $R^2$ improves a bit to 44 percent, compared to the 35 percent of column (2).

Initial leverage acts as a proxy for the mean of the unconditional distribution of leverage decisions. In column (4) I add mean book leverage, $(\Sigma_{t=0}^{T-1} d_{i,t}/k_{i,t})/T$, as a regressor to the specification in column (2). Consistently, results show that the coefficient of initial leverage decreases close to zero, while the coefficient of mean leverage is around 1 and highly statistically significant. In addition, the adjusted $R^2$ for this specification increases to 58 percent. Finally, column (5) incorporates mean
leverage to equation (22) and further confirms previous results. The adjusted $R^2$ for the specification in column (5) goes up to 67 percent. The dissimilar $R^2$ of the different specifications highlights the importance of firm-specific fixed effects in the explanation of leverage as opposed to traditional determinants.\[6\]

Then, I study the impact of introducing time-varying determinants to the autoregressive model described in Equation (21) on the speed of mean-reversion of book leverage. That is, I replace the mean of leverage decisions, $\bar{d}_{i,t+1 \mid k_{i,t+1}}$, on initial leverage, $d_{i,0}/k_{i,0}$, mean leverage, $(\sum_{t=0}^{T-1} d_{i,t}/k_{i,t})/T$, profitability (operating profits), $\pi(k_{i,t}, z_{i,t})/k_{i,t}$, investment opportunities (market-to-book ratio), $v_{i,t}/k_{i,t}$, volatility of operating income, $\sigma_{\pi_{i,t}}$, and lagged dividends, $div_{i,t}/k_{i,t}$. The numbers in parentheses are the $p$-values for the regression coefficients. *Statistical significance at the 1 percent level.

\[
\begin{array}{c|c|c|c|c|c}
\text{Variable} & (1) & (2) & (3) & (4) & (5) \\
\hline
\text{Intercept} & 0.5806 & 0.1932 & 0.2870 & -0.0001 & 0.0720 \\
& (0.0000)* & (0.0000)* & (0.0000)* & (0.4169) & (0.0000)* \\
\text{Initial leverage} & 0.5956 & 0.5583 & 0.0222 & -0.0017 & \\
& (0.0000)* & (0.0000)* & (0.0000)* & (0.0013)* & \\
\text{Mean leverage} & 0.9980 & 0.9841 & & & \\
& (0.0000)* & (0.0000)* & & & \\
\text{Profitability} & 0.2437 & 0.3134 & & & \\
& (0.0000)* & (0.0000)* & & & \\
\text{Market-to-book ratio} & -0.0344 & -0.0295 & & & \\
& (0.0000)* & (0.0000)* & & & \\
\text{Operating income volatility} & -0.1702 & -0.1713 & & & \\
& (0.0000)* & (0.0000)* & & & \\
\text{Lagged dividends} & -1.3751 & -0.7266 & & & \\
& (0.0000)* & (0.0000)* & & & \\
\text{Adjusted $R^2$} & 0.10 & 0.35 & 0.44 & 0.58 & 0.67 \\
\hline
\end{array}
\]

Notes: The simulated panel is composed of 100 firms and is divided into 10 types of 10 identical firms. Each type is different in parameter $\sigma_{\varepsilon}$, which ranges from 0.1 to 0.7. This parameter captures the volatility of profit shocks that firms in each group face. Each firm is simulated over 1,000 periods after discarding the first 200 observations to eliminate the influence of an arbitrary initial point. The simulation is parameterized at the values estimated in Section V. The table shows the regression coefficients of book leverage, $d_{i,t+1}/k_{i,t+1}$, on initial leverage, $d_{i,0}/k_{i,0}$, mean leverage, $(\sum_{t=0}^{T-1} d_{i,t}/k_{i,t})/T$, profitability (operating profits), $\pi(k_{i,t}, z_{i,t})/k_{i,t}$, investment opportunities (market-to-book ratio), $v_{i,t}/k_{i,t}$, volatility of operating income, $\sigma_{\pi_{i,t}}$, and lagged dividends, $div_{i,t}/k_{i,t}$. The numbers in parentheses are the $p$-values for the regression coefficients. *Statistical significance at the 1 percent level.

Then, I study the impact of introducing time-varying determinants to the autoregressive model described in Equation (21) on the speed of mean-reversion of book leverage. That is, I replace the mean of leverage decisions, $\bar{b}_{ML}$, in the aforementioned equation by the usual leverage determinants. The underlying idea of this exercise is that if traditional determinants of book leverage play an important role in the determination of the value to which book leverage mean-reverts, then their exclusion should considerably decrease the speed of mean-reversion of leverage. The cause of this is that firm leverage would be mean-reverting to a value that differs from the one specified by the econometrician.

Accordingly, I estimate the following autoregressive model of book leverage:

\[
\frac{d_{i,t+1}}{k_{i,t+1}} = a_1 \left[ b_0 + b_1 \frac{d_{i,0}}{k_{i,0}} + b_2 \left( \frac{1}{T} \sum_{t=0}^{T-1} \frac{d_{i,t}}{k_{i,t}} \right) + b_3 \frac{\pi(k_{i,t}, z_{i,t})}{k_{i,t}} + b_4 \frac{v_{i,t}}{k_{i,t}} + b_5 \sigma_{\pi_{i,t}} + b_6 \frac{div_{i,t}}{k_{i,t}} \right] \\
- (1-a_1) \frac{d_{i,t}}{k_{i,t}} + \varepsilon_{i,t+1}
\]  
(23)

where the variables are those defined in Equation (22). Results are presented in Table IV. Column (4) exhibits the estimation results for a specification that considers...
only initial leverage and mean leverage (i.e. the most important determinant according to results in Table III). The speed of mean-reversion is 35.87 percent per year, which is close to that found for the case of a single firm in Equation (21).

Columns (2) and (3) show that excluding mean leverage substantially reduces the speed of mean-reversion to 19.79 and 19.16 percent per year, respectively. Moreover, column (1) shows that if initial leverage (i.e. the proxy for mean leverage) is also excluded, then the speed of mean-reversion falls even further to 12.77 percent per year. This result is consistent with those of Fama and French (2002), who use specifications similar to the one in column (1) and find speeds of mean-reversion of book leverage between 10 and 18 percent per year.

Finally, column (5) presents the results of adding the traditional determinants of book leverage to the specification in column (4). The consequence of this is a small increase in the speed of mean-reversion of book leverage from 35.87 to 37.11 percent per year.

This subsection shows that model results are consistent with Lemmon et al. (2008). That is, traditional determinants of capital structure, mainly profitability and market-to-book ratio, have limited power to explain leverage decisions and most of the variation in leverage is explained by the constant value around which leverage oscillates. In the context of the dynamic model, this mean value is determined by the structural characteristics of the firm, such as the curvature of the production function ($\alpha$), the depreciation rate ($\delta$), the volatility ($\delta_{\epsilon}$) and persistence ($\rho_z$) of profit shocks, the

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Speed of mean-Reversion</td>
<td>0.1277</td>
<td>0.1979</td>
<td>0.1916</td>
<td>0.3587</td>
<td>0.3711</td>
</tr>
<tr>
<td></td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.2137</td>
<td>0.2035</td>
<td>-0.1148</td>
<td>0.0000</td>
<td>-0.0444</td>
</tr>
<tr>
<td></td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.4880)</td>
<td>(0.0000)*</td>
</tr>
<tr>
<td>Initial leverage</td>
<td>0.5739</td>
<td>0.6424</td>
<td>-0.0062</td>
<td>-0.0019</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.00018)*</td>
<td>(0.0487)**</td>
<td></td>
</tr>
<tr>
<td>Mean leverage</td>
<td></td>
<td></td>
<td></td>
<td>1.0062</td>
<td>1.0240</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
</tr>
<tr>
<td>Profitability</td>
<td>4.0907</td>
<td>2.0559</td>
<td>0.0111</td>
<td></td>
<td>0.8243</td>
</tr>
<tr>
<td></td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Market-to-book ratio</td>
<td>0.1063</td>
<td>0.0346</td>
<td></td>
<td></td>
<td>0.0000</td>
</tr>
<tr>
<td></td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating income volatility</td>
<td>-1.3580</td>
<td>-0.5405</td>
<td>-0.0604</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged dividends</td>
<td>-0.4141</td>
<td>-0.1962</td>
<td>-0.0101</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0000)*</td>
<td>(0.0000)*</td>
<td>(0.0172)*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Half-life</td>
<td>5.07</td>
<td>3.14</td>
<td>3.26</td>
<td>1.56</td>
<td>1.49</td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.75</td>
<td>0.73</td>
<td>0.77</td>
<td>0.76</td>
<td>0.81</td>
</tr>
</tbody>
</table>

Notes: The simulated panel is composed of 100 firms and is divided into 10 types of 10 identical firms. Each type is different in parameter $\sigma_{\epsilon}$, which ranges from 0.1 to 0.7. This parameter captures the volatility of profit shocks that firms in each group face. Each firm is simulated over 1,000 periods after discarding the first 200 observations to eliminate the influence of an arbitrary initial point. The simulation is parameterized at the values estimated in Section V. The table shows the regression coefficients of book leverage, $d_{i,j+1}/k_{i,j+1}$, on initial leverage, $d_{i,0}/k_{i,0}$, mean leverage, $(\Sigma_{j=0}^{T-1}d_{i,j}/k_{i,j})/T$, profitability (operating profits), $\pi(k_{i,j},z_{i,j})/k_{i,j}$, investment opportunities (market-to-book ratio), $v_{i,t}/k_{i,t}$, volatility of operating income, $\sigma_{\epsilon_{i,t}}$, lagged dividends, $div_{i,t}/k_{i,t}$, and lagged book leverage, $d_{i,t}/k_{i,t}$. The numbers in parentheses are the p-values for the regression coefficients. *,**Statistical significance at the 1 and 5 percent level, respectively.
income tax rate \((\tau_c)\), etc. The variation of any of these primitive characteristics changes the level to which leverage mean-reverts, as I showed above with the volatility of profits.

C. Convergence and stability of leverage

By constructing four portfolios of firms sorted according to their current leverage, Lemmon et al. (2008) present two interesting features of the data: convergence and stability of leverage. The former refers to the fact that firms with relatively high (low) leverage are likely to return to more moderate levels of leverage over time, while the latter implies that firms with relatively high (low) leverage tend to keep relatively high (low) leverage for long periods of time (more than 20 years). I study whether these characteristics of the data appear in the context of the dynamic model. I follow the procedure used by the aforementioned authors to construct the four portfolios (i.e. “very high,” “high,” “medium,” and “low” leverage portfolios). The sample for this analysis is the simulated panel of firms described in the previous subsection.

Figure 2 shows the actual book leverage paths created by the simulated panel of firms. It is evident that the dynamic model generates leverage decisions characterized by both convergence and stability of leverage. In the context of the dynamic model, convergence of leverage is due to the mean-reverting property of leverage decisions described in Subsection VI.A. That is, when leverage decisions of the different firms are averaged in the portfolios, their fluctuation around the mean creates the observed convergence. With a speed of mean-reversion around 35 percent per year, most of the

![Actual Book Leverage Portfolios](image)

**Notes:** The figure displays the actual book leverage paths generated by the dynamic model. The four portfolios (i.e., “very high,” “high,” “medium,” and “low” leverage portfolios) are constructed by sorting firms according to their current leverage. Each line represents the average actual book leverage of each portfolio. The sample in this analysis includes 100 firms, which are simulated at the estimated values of the parameters. This sample is divided into 10 different types, each of which includes 10 identical firms. The types differ in parameter \(\sigma_v\), which ranges from 0.1 to 0.7 and represents the volatility of profit shocks. Each firm is simulated over 1,000 periods after removing the first 200 observations to eliminate the influence of an arbitrary start.
convergence occurs in the first five to seven years after portfolio formation. Regarding
the stability of leverage, each type of firm in the panel has a different mean value
around which leverage oscillates. That is, the different structural assumptions for each
type of firm (i.e. profit volatility, σε, ranging from 0.1 to 0.7) create a type-specific
constant value toward which leverage mean-reverts. Thus, the values to which the four
lines in Figure 2 converge are the average of the unconditional means of leverage
decisions of all firms included in the corresponding portfolio.

Next, I construct the “unexpected leverage” portfolios. First, I regress book leverage
on profitability, market-to-book ratio, volatility of operating income, and lagged
dividends. Second, I use the regression residuals (i.e. the unexpected leverage) to sort
firms into the four portfolios. Finally, I follow the average book leverage of each
portfolio during the next 20 years. The objective of this procedure is to remove the
observable heterogeneity associated with traditional determinants of leverage. That is,
the expectation is to find that there is less cross-sectional variation in leverage in the
period of portfolio formation and that the four averages converge to a single line over
time. Figure 3 presents the unexpected book leverage paths generated by the panel of
firms and shows that the results are almost identical to those of Figure 2. Thus, the
regression residual explains most of the variation in leverage across firms in the panel,
and the usual time-varying determinants have little power to explain such variation[7].

This subsection confirms the results of the previous one. The dynamic model
generates firm decisions that are consistent with the features of the data described by

![Figure 3. Unexpected book leverage portfolios](image)

**Notes:** The figure displays the unexpected book leverage paths generated by the dynamic
model. The four portfolios (i.e., “very high,” “high,” “medium,” and “low” leverage
portfolios) are constructed by sorting firms according to their current leverage. Each line
represents the average unexpected book leverage of each portfolio. The sample in this
analysis includes 100 firms, which are simulated at the estimated values of the parameters.
This sample is divided into 10 different types, each of which includes 10 identical firms.
The types differ in parameter σε, which ranges from 0.1 to 0.7 and represents the volatility of
profit shocks. Each firm is simulated over 1,000 periods after removing the first 200
observations to eliminate the influence of an arbitrary start.
Lemmon et al. (2008). In other words, the constant value around which leverage oscillates explains most of the variation in leverage and traditional determinants of capital structure, mainly profitability and market-to-book ratio, have limited power to explain leverage decisions. As previously explained, the time-invariant value is a function of the fundamental characteristics of the firm.

VII. Conclusion
I estimate a dynamic structural model of the firm based on the trade-off theory of capital structure that features endogenous investment, leverage, and payout decisions. The model explicitly includes the benefits (i.e. interest tax shields) and the costs (i.e. costs of financial distress) of debt, as well as the costs of external capital. I use the EMMs to estimate the structural parameters that best fit the characteristics of the data.

In agreement with Lemmon et al. (2008), the dynamic model suggests that the power of traditional leverage determinants, mainly profitability and market-to-book ratio, to explain leverage decisions is fairly limited and most of the cross-sectional leverage variation is explained by unobserved firm-specific fixed effects. An implication of these findings is that traditional capital structure studies might be missing relevant leverage determinants. The structural approach I use in this paper allows me to shed light on this issue, suggesting that those missing determinants are given by the primitive features of the firm, such as the elasticity of capital, the capital depreciation rate, the volatility and persistence of profit shocks, etc.

Overall, my dynamic model provides a theory-based explanation for the unobserved firm-specific components that govern the cross-sectional variation in leverage. That is, it helps us to understand more completely the role played by the primitive characteristics of the firm versus the traditional time-varying factors in leverage decision making. These results highlight the importance of structural modeling as a complement of the reduced-form approach in corporate finance.

Notes
1. See, for instance, Fama and French (2002), Flannery and Rangan (2006), Huang and Ritter (2009), and DeAngelo et al. (2011).
2. The list of important papers in this literature is vast, including, but not limited to, Long and Malitz (1985), Shyam-Sunder and Myers (1999), Fama and French (2002), and Flannery and Rangan (2006).
3. After this filter, the sample has 109,049 firm-year observations.
4. The URL is: www.u.arizona.edu/126amenichi/Papers/SNP.pdf
5. Volatility of operating income is defined as the standard deviation of the previous three years of operating income, \( \pi(k_i, z_i)/k_i \).
6. In an unreported study, I perform a variance decomposition of book leverage to ascertain the explanatory power of the traditional determinants (i.e. profitability, market-to-book ratio, etc.) and of the constant firm-specific factors (i.e., initial leverage and mean leverage). The results further confirm the importance of the latter as leverage determinants and the relatively small role played by the former.
7. In unreported results, I repeat the previous experiment including the volatility of profit shocks, \( \sigma_e \), as a regressor. As expected, that parameter correctly captures most firm heterogeneity and the four lines converge almost completely over time.
References

Further reading
Appendix. Implementation of the model
The model in this paper cannot be solved in closed-form. However, its solution can be numerically approximated. The numerical solution of the dynamic model is obtained via value function iteration, as described by Judd (1998).

In order to implement the model, I need to discretize the state space of $k$, $d$, and $z$. I let the capital stock, $k$, belong to the set:

$$
\bar{k} = \left[ \bar{k}, \bar{k}(1-\delta)^{1/2}, \bar{k}(1-\delta), \ldots, \bar{k}(1-\delta)^{20} \right]
$$

where $\bar{k}$ satisfies Equation (8). The stock of debt, $d$, lies in the set:

$$
\bar{D} = \left[ 0, \frac{1}{40} \bar{k}, \ldots, \frac{39}{40} \bar{k}, \bar{k} \right]
$$

with $\bar{k}$ also satisfying Equation (8). This choice of the discretization of the state space of $k$ and $d$ reflects the fact that the investment decision is a considerably non-linear function of the profit shock while the leverage decision, on the contrary, is a relatively more linear mapping of $z$.

The AR(1) process for the profitability shock, $z$, defined in Equation (1) is transformed into a discrete-state Markov chain following the quadrature method of Tauchen (1986). I let $z$ have 21 points of support in the set:

$$
\bar{Z} = \left[ \frac{c}{1-\rho_z} - 3 \frac{\sigma_z}{\sqrt{1-\rho_z^2}}, \frac{c}{1-\rho_z} + 3 \frac{\sigma_z}{\sqrt{1-\rho_z^2}} \right].
$$

Corresponding author
Dr Amilcar Menichini can be contacted at: aamenich@nps.edu

For instructions on how to order reprints of this article, please visit our website:
www.emeraldgrouppublishing.com/licensing/reprints.htm

Or contact us for further details: permissions@emeraldinsight.com