Debt Maturity Choice and Aggregate Growth

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Draft:

We find that a measure of aggregate corporate debt maturity choices strongly predicts real GDP growth. The new measure compares well with other strong GDP predictors from recent literature, is no less robust/stable, and distinct from spread-related variables. We develop a novel theory of firm debt maturity choice explaining these findings: In anticipation of inefficient firm operations during non-contractible negative expected profitability states, long-term lenders charge more interest. When choosing debt maturity, firms balance this against the higher cost of refinancing short-term debt. Maturity choices are more sensitive to profit anticipation whereas default spreads are more sensitive to profit dispersion.
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It is likely an understatement to observe that a large portion of the macroeconomics literature is devoted to forecasting the business cycle. Earlier work identified that, beyond containing an autoregressive component, the aggregate growth rate of real GDP is linked to financial and real market prices.[1] Subsequent to the great financial crisis, a series of important papers demonstrated that corporate bond market spreads have exceptional predictive power for aggregate growth (Gilchrist, Yankov and Zakrajšek, 2009; Gilchrist and Zakrajšek, 2012; Greenwood and Hanson, 2013; López-Salido, Stein and Zakrajšek, 2017).

Our contribution to this literature is twofold. We introduce a new information-containing variable to the important literature on predicting aggregate growth and

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[1]Harvey (1988); Estrella and Hardouvelis (1991); Friedman and Kuttner (1992); Estrella and Mishkin (1998); Friedman and Kuttner (1998); Hamilton and Kim (2002); Stock and W Watson (2003); Ang, Piazzesi and Wei (2006).

provide theoretical microfoundations for the new variable's strong and distinct forecasting power. We use data from Mergent FISD to calculate a quarterly ratio, f_{sl}, of the number of newly issued short-maturity ($\leq$ 5 years) rated corporate bonds over newly issued long-maturity ($\geq$ 10 years) rated bonds. f_{sl} is strongly and negatively associated with GDP growth. A one standard deviation change in f_{sl} from its unconditional mean predicts a decline of roughly 0.2% in the following quarter and a decline of 0.5% or more over the following year. The forecasting power of f_{sl} for GDP growth, and its economic significance, rivals that of spread-based predictors.[2] Importantly, the predictive power of f_{sl} is largely robust to the inclusion of spread-based market variables in a growth forecasting regression. This suggests that the information contained in f_{sl} about future growth is distinct from the information in spread-based variables. Moreover, f_{sl} is no less robust (and, in some cases, perhaps more so) than other predictive variables to the inclusion/exclusion of outliers and subperiods prior to 2020.[3]

Equally-weighting bond maturity choices when constructing f_{sl} appears to be crucial. A similar, albeit value-weighted, measure (using the total offering amount) has only half of the explanatory power of f_{sl} for forecasting GDP and is subsumed by the latter when both are included in a forecasting regression. This suggests that much of the predictive power comes from the maturity choices of smaller firms. Relatedly, the forecasting power of f_{sl} for GDP is unrelated to the government debt duration variable of Greenwood, Hanson and Stein (2010) (argued to be inversely related to the bond maturity choices of larger firms).

We provide a simple stylized model that helps to explain the various empirical findings summarized above. In the model, both long- and short-term debt exhibit frictions that the firm must trade off when initially financing a project. We show that, under long-term financing of a multi-period project, a firm that maximizes shareholder value may choose to operate in future negative net present value (NPV) states. This "overinvestment" problem arises because, for shareholders, investing in continued operations has a positive option value even after profit expectations decline and the firm is no longer expected to meet its debt obligations.

[2]These include the treasury term spread, the BAA-AAA default spread, the Greenwood and Hanson (2013) measure of high-yield bond issuance, the GZ spread and excess bond premium (EBP) measures developed in Gilchrist and Zakrajšek (2012), and the Chicago Fed's National Financial Conditions Index.

[3]Our data spans 1982Q2 to 2020Q1. We intentionally exclude available data from the COVID-19 era (2020Q2 and after) from our analysis because government intervention in the US market for newly issued bonds comprised a pronounced distortion of typical cyclical trade-offs in corporate debt maturity choices.

If debt covenants cannot fully address contingencies of shifting expectations (i.e., expectations are not contractible), long-term lenders will require an otherwise higher interest coupon to compensate them for inefficiencies that are incentivized by the capital structure. Short-term financing, by contrast, is less vulnerable to contract-induced operational inefficiencies because the firm will not seek new financing and cease operations when the value of continuing a project is less than the amount required to finance its continuation. The asymmetric potential for operational inefficiencies reduces the present value to shareholders of a long-term financing arrangement relative to short-term debt. The latter, however leads to higher overall transaction costs (because it requires more financing transactions per project).

We show that balancing the costs of inefficient operations under long-term debt against the higher transaction costs of repeated short-term financing amounts to a put option valuation exercise. The option is tantamount to replacing long-term with short-term financing and comprises "insurance" against states of inefficient project operation. The cost of the option is the additional transaction cost of rolling over short-term debt. Firms with high (resp. low) option value relative to its cost will opt for short-term (resp. long-term) debt. If expectations of future economic conditions are depressed, the put option value is higher because of a higher propensity for continued project operations in inefficient states — this leads to greater use of short-term debt. It is through this anticipatory channel of future profitability that aggregating firm-level financing decisions is linked to macroeconomic growth.[4]

To investigate the ability of the theoretical channel identified above to explain the empirical findings, we model an economy with overlapping generations of heterogeneous two-period projects. Although the model is highly stylized, it is possible to find seemingly reasonable economic parameters that result in a crude match to the unconditional share of short-term rated bond issuance. We confirm within the context of the model that this share predicts future GDP growth as long as the latter is correlated (even weakly) with profit *expectations* held by a typical firm's managers and lenders. Put differently, firms' debt maturity choice depends on forming firm-level profit expectations and, to the extent that these

[4] Roughly 50% of CFOs surveyed by Graham and Harvey (2001) agree that it is important or very important to "...issue long-term debt to minimize the risk of having to refinance in "bad times". This is consistent with linking debt maturity choice to the perceived distribution of future profits.

expectations individually comprise weak signals of future aggregate outcomes, aggregate maturity choices will predict future GDP.

We demonstrate that model default spreads on long-maturity bonds, when aggregated across firms, also reflect aggregate profit expectations, but less so under extreme scenarios.[5] In a simulated regression setting, where only profit expectations are time-varying, our model proxy for f_{sl} is a better predictor of future GDP than the aggregate default spread. Default spreads, however, are also sensitive to changes in risk perceptions and aggregate risk tends to move inversely with aggregate outcomes (Jurado, Ludvigson and Ng, 2015). Indeed, assuming firm profit risk is countercyclical, we show that default premia provide a complementary significant channel to f_{sl} for forecasting future GDP. Using both anticipatory channels (expected firm profits *and* future profit riskiness) rationalizes our empirical findings and provides a microfoundation for understanding the behavior of f_{sl} as a predictor of the business cycle.

Related Literature

Prior literature identifies a number of useful predictors of macroeconomic activity. Among these are: the slope of the treasury (risk-free) term structure (Harvey, 1988; Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998; Hamilton and Kim, 2002); short-term treasury rates (Ang, Piazzesi and Wei, 2006); default/credit spreads (Friedman and Kuttner, 1992; Gilchrist, Yankov and Zakrajšek, 2009; Gilchrist and Zakrajšek, 2012; Greenwood and Hanson, 2013; López-Salido, Stein and Zakrajšek, 2017); and the Chicago Federal Reserve Bank's National Financial Conditions Index (NFCI) measure (Adrian, Boyarchenko and Giannone, 2019). In addition, standard neo-Keynesian macro models seeking to understand the Phillips Curve and Taylor Rules as functions of monetary policy can be viewed in reduced-form as vector auto-regressions of real GDP, the short-term treasury rate, and inflation (Rudebusch and Wu, 2008; Bekaert, Cho and Moreno, 2010; Campbell, Pflueger and Viceira, 2020). Whereas the majority of prominent growth forecasting variables in the literature are based on asset prices,

[5] The lower sensitivity of default spreads to future profit expectations is partly endogenous: Firms with low profit expectations will not issue long-term bonds and will thus not contribute to the average default premium on long-term bonds. A similar argument may explain why value-weighting reduces the forecasting power of f_{sl}: Larger firms tend to be more profitable, meaning that the variation in a value-weighted maturity choice variable will be relatively muted.

ours (f_{sl}) is an aggregate of firm choices.[6] As shown in the empirical section, the explanatory power of f_{sl} is robust to the inclusion of standard predictors.

In terms of basic structure, our model is closest to Flannery (1986), Diamond (1991), and Rajan (1992). All three papers consider a three date (two period) model where the firm must decide at date 0 between short- or long-term debt financing, and where some new information about date 2 payoffs arrives at date 1.[7] The main inefficiency in our model comes from the firm's inability to commit to abandoning negative NPV projects (i.e., avoid "overinvestment"), traded off against costs of refinancing short-term debt at date 1. In Flannery (1986), Diamond (1991), and Rajan (1992), the key friction is private information that the firm may have about date 1 uncertainty. Although the three papers differ on the additional frictions introduced, absent these, good firms can try to signal their quality by borrowing short-term and a pooling equilibrium ensues.[8] An important takeaway is that introducing costs to short-term financing may separate firms' maturity choice by quality such that the best firms favor short-term debt. Thus, this set of models does not generally provide a clear *positive* link between quality and long-term debt issuance. In this sense, our model is both distinct and aligns better with the specific stylized facts we seek to explain.

More broadly, we contribute to the large theoretical literature on debt maturity trade-offs. Starting with Leland and Toft (1996), many papers in this genre focus on examining these tradeoffs in the presence of tax benefits (of debt) and bankruptcy costs.[9] The conclusions tend to depend on the particulars of how debt is financed (e.g., continuously or in a single lump-sum), whether its level can change through time (i.e., whether capital structure can be re-optimized), financing costs (for debt and/or equity), whether or not the firm can commit to a borrowing strategy, the asset evolution assumptions, and the potential for risk-shifting through future investments.

One common feature to many models in this literature is that post-financing

[6]It is natural that durable asset prices ought to anticipate future outcomes. It is equally natural that "durable choices" will reflect the same. Ours is not the first choice-based variable to be noted as a good predictor of aggregate growth. Housing starts and unemployment, for instance, have also been noted for their growth forecasting power (e.g., Ang, Piazzesi and Wei, 2006, and references therein).

[7]Hart and Moore (1995) and Diamond and He (2014) also use the same structure. We discuss them below in more detail.

[8]Flannery (1986) additionally considers refinancing transaction costs, Diamond (1991) considers loss of non-transferable cash flow rights in liquidation, and Rajan (1992) considers effort costs and the possibility of debt renegotiation.

[9]These include He and Xiong (2012); Geelen (2016); Chen, Xu and Yang (2021); Dangl and Zechner (2021); DeMarzo and He (2021); Benzoni et al. (2022).

decisions available to firm managers can lead to conflicts of interest between long-term debt holders and shareholders and, consequently, ex-post inefficient outcomes. This is also present in our model, where the inability to commit to an efficient operating policy leads to overinvestment in unprofitable projects, though our mechanism contrasts with the ex-post inefficiency channels considered by other models (i.e., future financing, asset substitution, and underinvestment). It is worth noting that the type of inefficiency we consider would be hard to address using bond covenants. Save for addressing material changes in the nature of the firm's business (i.e., type of industry), debt covenants rarely address direct investment or what could be deemed operational decisions, tending instead to address financial policy (dividends, security issuance, etc.) and changes in the firm's financial outcomes (Chava, Kumar and Warga, 2010). As such, covenants are unlikely to provide direct means for contracting on future firm profit expectations, the central source of friction in our model. In summary, to our knowledge, studying how debt maturity choice relates to operational inefficiencies caused by changing expectations is a novel contribution to the literature.

Another feature common to several models is the cyclicality of debt maturity (more short-term debt is issued during bad economic states).[10] In our setting, model firms and their lenders anticipate future firm profits based on information that is correlated with future GDP. Thus firms' decisions act as weak signals that, when aggregated, contain information that is otherwise unavailable. This is a fundamental departure from the typical assumption in models of cyclical debt maturity where firms adjust their financing to reflect the *current* economic environment based on information that is available to everyone. In such models, aggregate maturity choice and default spreads can, at best, be proxies for existing known predictors of GDP.

Our model ignores the usual trade-offs (tax benefits of debt versus bankruptcy costs). This feature is shared by three prominent exceptions to the tax-default costs paradigm: The "empire building" model of Hart and Moore (1995), the gap filling model of Greenwood, Hanson and Stein (2010), and the debt overhang model Diamond and He (2014). Though the setup in Hart and Moore (1995) is closest to ours, there are important key differences. First, the manager in Hart and Moore (1995) maximizes the physical size of the firm rather than shareholder

[10]For example, Yamarthy (2020), Dangl and Zechner (2021), Chen, Xu and Yang (2021) and Hu, Varas and Ying (2021).

value. Second, liquidation is never efficient in their model. These assumptions lead the firm to debt financing that exclusively employs long-term obligations. In Greenwood, Hanson and Stein (2010), lenders' maturity offerings compete against the government's maturity choice within a preferred investor habitat setting. Our empirical work in Section I suggests that this is not the main channel explaining the forecasting power of our measure. As in our model, Diamond and He (2014) are agnostic about the reasons for debt financing (and, therefore, optimal debt level). They, however, focus on exploring how inefficiencies introduced by debt overhang depend on debt maturity and the structure of asset volatility. As mentioned earlier, long-term debt inefficiency in our model arises from overinvestment rather than underinvestment. In contrast with the usual source of overinvestment considered in the literature (stemming from managerial agency problems like empire building, as in Jensen and Meckling, 1976), overinvestment borne of lender-shareholder conflict has received far less attention in the literature (see, for example, Mauer and Sarkar, 2005).

Organization of the paper

Section I presents our empirical work and contribution while Section II develops the theoretical framework, providing a possible microfoundation underlying our empirical findings. Section III concludes.

I. Empirical analysis

In this section, we report findings on the predictability of real GDP using aggregate corporate bond maturity choices. In particular, we demonstrate that, f_{sl} the ratio of the number of short- versus long-maturity bond issues is countercyclical and a strong predictor of future GDP. We show that the predictive power of this measure is not significantly subsumed by other predictors appearing in the literature. Indeed, a main takeaway from this section is that f_{sl} captures something distinct from existing measures, including those linked to credit spreads, bond risk premia, or financial distress. We also show that, v_{sl}, a dollar-weighted ratio of short- versus long-maturity bond is a weaker predictor of GDP. This suggests that the predictability of f_{sl} is driven by smaller firms. Indeed, we demonstrate that government bond maturity issuance choices, and therefore the "Gap-filling" theory of Greenwood, Hanson and Stein (2010), does not explain the dynamics of f_{sl}. Finally, we subject the predictive power of f_{sl} to various robustness tests and report that it performs well relative to recent noteworthy predictors.

A. Data

Data on corporate debt issuance, used to calculate the short- and long-term issuance statistics as well as the Greenwood and Hanson (2013) measure of high-yield bond issuance (LnHYShare), are obtained from Mergent FISD via WRDS.[11] Macroeconomic time series, including the treasury term spread, federal funds rate, consumer price index (CPI) growth, GDP growth, the Moody's BAA-AAA credit spread, and the NFCI index are obtained from FRED (St. Louis Federal Reserve Bank).[12] Data on the GZ spread and excess bond premium (EBP), developed in Gilchrist and Zakrajšek (2012), are taken from a Federal Reserve site.[13] Finally, we use CRSP data from WRDS to calculate MDUR, a measure of prevailing government treasury duration as developed by Greenwood, Hanson and Stein (2010) in their gap-filling theory of corporate maturity choice.

Our full quarterly data sample starts at 1982Q2 and ends at 2020Q1. The former is the earliest quarter during which all variables are available.[14] In calculating f_{sl} and v_{sl}, we only use rated bond issues. This is because, subsequent to the 1994 Riegle-Neal Act, issuance of unrated long-term debt has been negligible.[15] Also, we intentionally avoid using the few quarters of data available to us after 2020Q1 because of the extreme bond market intervention by the US Federal Reserve in March of 2020 (at the beginning of the COVID-19 period). As documented in Darmouni and Siani (2022), this intervention had profound implications for bond issuance and maturity choice that went far beyond the set of bonds eligible for

[11]We follow Greenwood and Hanson (2013) in employing the natural logarithm of the dollar share of high-yield bond issuance because, as they report, the log-measure has nominally better time-series predictive power. Similarly transforming the other measures we examine does not appear to improve their predictive power. In this sense, we are giving HYShare the greatest 'benefit of doubt' as a predictive variable.

[12]Growth variables are calculated by taking the the natural logarithm of the ratio of current to lagged levels. The lag is a quarter unless otherwise noted.

[13]`https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv`.

[14]There are a couple of missing quarters within this window for variables constructed from Mergent FISD bond issuance data (LnHYShare is missing in 1990Q2 while f_{sl} and v_{sl} are missing for 1983Q3). We linearly extrapolate these based on the two prior quarters to "fill in" the time series. This ensures that only contemporaneous information is used in the predictive regressions for GDP.

[15]Our Mergent FISD data covers public debt issues. It is possible or even likely that, after the 1994 Riegle-Neal Act banks have been able to offer more efficient competition over firms seeking longer-maturity unrated debt. Because we do not have access to privately issued debt data, which may compete with public unrated debt, we elected to focus only on rated debt.

the Fed's program.[16]

We only consider US corporate bonds with no conversion, put or exchangeability options. The maturity distribution of rated bonds in our sample is depicted in the cumulative distribution plot of Figure 1. Roughly 40% are issued with maturities below five years, while about the same number of bonds are issued with maturities of ten or more years. Correspondingly, we define short-maturity bonds as those with maturity (at issuance) less than or equal to five years, and long-maturity bonds as those with maturity greater than or equal to ten years (with maturities rounded to the nearest integer). These cutoffs reflect natural, albeit lumpy, maturity categories chosen by firms in practice as well as balanced proportions of the distribution of issued bonds.[17] Mergent FISD data is sparse prior to 1991Q1, with nearly half of those early quarters containing fewer than five rated bonds with maturity less than five years (and nearly one quarter containing none). To reduce potential noise created by data sparsity, we categorize all bonds with maturity less than 9.5 years, issued prior to 1991Q1, as "short-maturity".[18] In a given quarter, f_{sl} is defined to be the ratio of the *number* of short- to long-maturity bonds issued. By contrast, the ratio v_{sl} is defined to be the ratio of the dollar amount of short- to long-maturity bonds issued.

Summary statistics for the main variables we consider in the predictive regressions are presented in Table 1. Intuitively, measures of aggregate financial conditions anticipate aggregate economic conditions, and a host of recent papers has empirically established a strong link confirming this intuition. Three such measures are linked to information from the bond market (GZ, EBP, and LnHYShare).[19] A fourth measure, NFCI, aggregates over 105 measures of financial activity (including bond market information) and has been shown to be a robust predictor of GDP (Rogers and Xu, 2019). MDUR measures the duration of prevailing government treasury securities which, according to the gap-filling

[16]The bond issuance distortions resulting from the Fed's policy likely lasted well-beyond 2020Q2. Because 2020Q2 featured a ten standard deviation quarterly decline in GDP growth, followed by an eight standard deviation reversal in 2020Q3, including data from this period in our analysis is unlikely to be representative of bond market equilibrium dynamics.

[17]The ensuing analysis is robust to various definitions of maturity categories. For instance, the results are largely qualitatively unchanged if, following Duffee (1998), we instead define short- and long-maturity bonds as those with maturity (at issuance) less than seven years and greater than fifteen years, respectively.

[18]We do this only to reduce the chance of spurious empirical inference. Our results are robust to, instead, maintaining a strict definition of "short-maturity" (less than or equal to five years) between 1982Q2 and 1990Q4.

[19]EBP is a component of the GZ-index.

model Greenwood, Hanson and Stein (2010), can drive corporate bond maturity choice. Correlations between these variables with f_{sl} and v_{sl} are reported in Table 2. The contemporaneous regression adjusted R^2 of each of f_{sl} and v_{sl} with the other five variables in Table 2 is, respectively, 18.4% and 15.8%, suggesting sufficient independent variation in both variables to potentially differentiate them as economic indicators.[20]

The correlation between f_{sl} and v_{sl} is moderate but not high. This is because the distribution of offering amounts is severely skewed. For instance, the offering amount first quartile is \$10M while the median is fifteen times higher. The 90th percentile is over four hundred times larger than the tenth percentile. This suggests that v_{sl} is dominated by the offerings of larger firms and little influenced by over a quarter of the bond issues in the data set.

B. Main empirical results

Table 3 presents some of our key empirical findings. Only coefficients that are significant at the 5% level, or better, are denoted with asterisks. Each column reports regression coefficients for a predictive specification of the form

$$g_{t+1} = \beta_0 + \beta' \cdot y_t + \varepsilon_{t+1},$$

where g_{t+1} is quarterly real and seasonally adjusted GDP growth as reported at the end of quarter $t+1$. The number of observations across the specifications is constant (151 quarters). The dependent variable in the regressions is measured in percentage points while all explanatory variables are standardized to facilitate interpretation.[21]

The first predictive regression employs standard lagged macro variables that have emerged in the literature. These include the slope of the treasury yield curve or " Term spread" (Harvey, 1988; Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998; Hamilton and Kim, 2002); the level of the shortest maturity nominal risk-free interest rates represented by the federal funds rate (Estrella and Hardouvelis, 1991; Hamilton and Kim, 2002); Consumer Price Index (CPI) growth

[20]The adjusted R^2 from regressing each of GZ, EBP, and NFCI on the other two variables is, respectively, 56.7%, 67.6%, and 38.5%.

[21]For instance, a regression coefficient of β on explanatory variable X corresponds to an incremental GDP growth prediction of β in a quarter following one where X is one standard deviation above its time series mean.

which should be related to growth (i.e., the output gap) through the Philips Curve (Rudebusch and Wu, 2008; Bekaert, Cho and Moreno, 2010; Campbell, Pflueger and Viceira, 2020); and the corporate bond BAA-AAA default spread which can reflect macroeconomic uncertainty (Gilchrist, Yankov and Zakrajšek, 2009). Because GDP growth is mean-reverting, we include its lagged (standardized) value in the regression to control for the possibility that the predictive power of the other lagged variables does not arise from contemporaneous relationships with GDP growth. Before interpreting the results, it may be useful to note that regressing GDP growth on lagged GDP growth results in a coefficient of 0.285 and adjusted R^2 of 0.203. Relative to that, the R^2 in the first regression increases by only four percentage points, suggesting that the additional explanatory variables add modest predictive power beyond what is already in lagged GDP growth. Of the remaining predictors, the level of the Federal funds rate is the most powerful predictor. The slope of the treasury yield curve (term spread), BAA-AAA spread, and the inflation have less significant predictive value.

Regressions (2), (3) and (5)-(8) in Table 3 incorporate each of the variables in Table 2, save for MDUR.[22] The short- to long-maturity bond issuance ratio, f_{sl}, adds more incremental explanatory power, in terms of adjusted R^2, than any other added predictor (nearly twice as much incremental forecasting power than all but NFCI). By contrast, v_{sl}, a size-weighted version of f_{sl}, contributes significantly but less than all other predictors and its power is completely subsumed by f_{sl} (see regression 4). Inclusion of the spread-based derived variables (GZ, EBP, and NFCI), perhaps not surprisingly, diminishes the explanatory power of the BAA-AAA spread.

In regressions (9)-(11), the coefficient of f_{sl} (and its significance) remains stable (within a standard error) when combined with the other predictive variables. These regressions also confirm that the explanatory power in the spread-based derived variables is largely colinear (i.e., including only one of them is sufficient).

An overall takeaway from Table 3 is that f_{sl} compares well, in terms of predictive power for GDP growth, with other macro variables noted in the literature. In addition, the stability of its regression coefficient suggests that the information contained in f_{sl} that is relevant for predicting GDP growth appears to be largely orthogonal to the information contained in other explanatory variables.

[22]MDUR has no marginal predictive power when added to any of the regressions in Table 3. This is explored later.

The latter message is reinforced by the suite of predictive regressions in Table 4 featuring only the more recent predictive variables from the literature. The only variable that cannibalizes the explanatory power of f_{sl} for future GDP growth appears to be contemporaneous GDP growth, and the corresponding erosion in predictive power is modest. The consistent message across specifications is that a one standard deviation increase in f_{sl} above its long-run mean predicts a decline of roughly 0.21 percentage points in real GDP growth for the following quarter.

Connection to the gap-filling theory

Greenwood, Hanson and Stein (2010) provide evidence that the selection of newly issued US corporate bond maturity is influenced by the average duration of outstanding US treasury securities. The idea is that there is a limited market appetite for the various bond maturities and firms can benefit from better terms (e.g., lower interest rates) if their bonds are not "competing" with treasury securities of similar maturity. In other words, when the average duration of treasury securities is unusually high, firms will "fill the gap" and issue more short-term bonds.

It is natural to ask whether the explanatory power of f_{sl} derives from this theory. Specifically, if the US government issues more long-maturity bonds (or purchases back short maturity bonds) in anticipation of a downturn, then the gap filling theory would predict that this anticipation will be reflected by an increase in f_{sl}.

The correlation of f_{sl} with MDUR is essentially zero (see Table 2), casting some doubt on MDUR being a primary driver of f_{sl}.[23] To investigate whether MDUR can predict GDP growth, and whether the predictive power of f_{sl} arises through some relationship with MDUR, we run the growth prediction regressions using lagged MDUR as well other lagged variables. Columns (1)-(5) in Table 5 report the results. The first regression demonstrates that, indeed, outstanding treasury securities' aggregate duration does forecast growth in a manner that is consistent with the gap filling theory: High duration of outstanding government securities predicts lower GDP growth. Regressions (2)-(5), however, suggest that this relationship is subsumed by other standard predictive macro variables.[24] We

[23] Greenwood, Hanson and Stein (2010) compare MDUR with a measure of average corporate bond duration calculated using Federal Reserve data on outstanding non-financial firm debt. By contrast, f_{sl} and v_{sl} are calculated using only newly issued corporate debt.

[24] A contemporaneous regression of MDUR on the remaining five explanatory variables in regression

note that in regression (4) the coefficient of f_{sl} is consistent with those in Tables 3 and 4 (i.e., the presence of MDUR does not significantly impact the explanatory power of f_{sl}).

In columns (6) and (7) of Table 5 we regress f_{sl} on MDUR, controlling for other variables (including lagged f_{sl}). Here too, there appears to be no relationship between MDUR and our measure of interest, suggesting that the predictive power of f_{sl} arises from something other than the gap filling theory.

C. Robustness

Figure 2 depicts key standardized macro variables used in the predictive regressions throughout the sample period. One-quarter ahead standardized GDP growth is plotted against each variable. In the case of f_{sl}, the shock in 2008q3, as the Great Financial Crisis began to unfold, was more than five standard deviation from the time-series average. Similar movements are observed with EBP, GZ, and NFCI, around the same period but conspicuously absent with LnHYShare. A natural concern with the preceding regression analyses is that the forecasting power of f_{sl}, or that of any other variable, depends on the regression specification or is driven by an outlier quarter or outlier year in the sample. We investigate this possibility in several ways.

First, we compare the statistical forecasting power of each predictor within a series of predictive regressions. We do this in the full sample (1982-2019) and two sub-samples (1982Q2-2000Q4 and 2001Q1-2020Q1). For each (sub)sample and each predictor among f_{sl}, LnHYShare, GZ, EBP, and NFCI, we regress quarterly GDP against the lagged predictor and every combination of the following lagged control variables: the treasury term spread, the Federal funds rate, Consumer Price Index growth, Moody's BAA-AAA bond yield spread, and real GDP growth. In Table 6, the absolute t-statistic of the candidate predictor is reported for specifications yielding the largest/smallest predictor t-stat magnitude; the last column report the largest adjusted R-squared across specifications. For example, across full-sample GDP forecasting regressions using LnHYShare and every combination of the control variables, the regression yielding the largest (smallest) magnitude t-stat for LnHYShare had $|t| = 4.666$ ($|t| = 1.722$). This suggests that the forecasting power of LnHYShare, while high in some instances, can be

(3) of Table 5 yields an adjusted R^2 of 67%.

subsumed by "classic" predictors. The regression with the highest adjusted R^2 yielded Adj $R^2 = 0.276$. This can be compared across subsamples and predictors. From this exercise we see that, by all measures, f_{sl} is the strongest predictor of GDP in the second half of the sample. In the first half of the sample, although its statistical strength as a forecasting variable falls dramatically, f_{sl} is comparable to GZ and EPB (and perhaps also NFCI). Across all subsamples, f_{sl} exhibits the least deterioration in forecasting power (measured as the difference between highest and lowest t-stat magnitudes).

In a second exercise, we fix a specification for a predictive regression and report on how the removal of a quarter or a calendar year from the sample impacts the macro variable's forecasting power in the remaining sample. For instance, consider the regression that resulted in the highest magnitude full-sample t-statistic ($|t| = 6.074$) for f_{sl} in Table 6.[25] If one sequentially removes a single quarter from the sample, re-running the regression each time, then the lowest magnitude t-statistic for f_{sl} among this series of regressions is 4.419. This indicates that, while there are some quarters in the sample that are very influential for imputing the forecasting power of f_{sl}, the overall significance of f_{sl} in this specification is not driven by a single outlier quarter. A similar exercise that instead sequentially removes an entire calendar year from the sample results in a lowest magnitude t-statistic of 3.200 for f_{sl}. This too is reassuring in that the forecasting power for f_{sl} does not depend entirely on one year in the sample.

Table 7 reports the result of a similar analysis for various predictive macro variables and various specifications: The specification with the highest (magnitude) t-test regression from Table 6;the specification with the highest adjusted R^2 regression from Table 6; the univariate forecasting regression with only one explanatory variable (the lagged predictive variable); and the bivariate forecasting regression with only lagged GDP and lagged predictive variable as explanatory variables. It should be clear from Table 7 that, across a host of specifications, f_{sl} consistently retains a highly significant degree of forecasting power. By contrast, for each of the other variables, there are always specifications for which removing a quarter or a calendar year from the sample results in insignificant or marginally significant forecasting power.

We conclude from these exercises that f_{sl} is as robust a predictor for growth as

[25]This happens to be the regression of GDP growth against lagged f_{sl}, Fed Funds rate, CPI growth, and the BAA-AAA spread.

any of the other macro variables thus far identified in the literature. In Appendix A, we extend the forecasting horizon to annual GDP growth and report that the predictive power of f_{sl} demonstrated in Tables 3 and 4 remains strong: A one standard deviation increase in f_{sl} predicts a decline of 50 to 80 basis points in annual GDP (depending on the specification). In Table A3, we report the results of repeating the last regression from each of Tables 3, A1, 4, and A2 using Newey and West (1987) standard error adjustments (with a four quarter lag). In all cases, the coefficients on f_{sl} remain highly significant. Beyond this we also considered the measures of macro uncertainty developed in Jurado, Ludvigson and Ng (2015) because of their impressive predictive power for GDP as documented in Rogers and Xu (2019). In our (unreported) tests, it seems that GZ, EBP, and NFCI subsume the predictive power of macro uncertainty measures. Like these latter measures, macro uncertainty does not materially impact the explanatory power of f_{sl}.

II. Model

There are three dates, $0, 1$ and 2, and two periods. At each of dates 0 and 1, a firm must invest c to finance the operations of a project. For simplicity, we assume that financing is secured to a project and use the terms 'project' and 'firm' interchangeably. Although information at the three dates may not be public, it is assumed to be symmetric across all firm decision-making stakeholders (lenders and firm managers).[26]

At dates 1 and 2 the operating project produces cash flow v_1 and $\tilde{v}_2$, respectively, with the former quantity known and the latter quantity a random variable. It is assumed that $v_1 > c$. Because we assume that one-period risk-free interest rates are zero and that all firm stakeholders are risk-neutral, neglecting financing costs, the date 0 net present value (NPV) from operating the project through both periods is simply $(v_1 - c) + E[\tilde{v}_2 - c]$, where $E[\cdot]$ denotes an expectation operator.

At date 1, new and non-contractible information, $\mathcal{I}_1$, arrives and is available to all firm stakeholders. Define $\tilde{\mu} = E[\tilde{v}_2 \mid \mathcal{I}_1]$ to be the conditional expectation of second period project profits at date 1. In particular, it may be that $\tilde{\mu} < c$, in

[26] One could rationalize this through a due-diligence cost paid by lenders (or their underwriters or informed investors), and incorporated into lenders' required rate of return. The cost can be trivial as long as it is finite so that it would be prohibitive for any single entity to pay it across all firms in the economy.

which case a decision to continue to operate the project at date 1 has a negative NPV.

The firm has to decide at date 0 how to initially finance its project. Specifically, it must raise c. To do that, it can issue a one-period risk-free bond (because $v_1 > c$ and interest rates are 0), and then decide based on the new information, $\mathcal{I}_1$, whether to raise a second, possibly risky, one-period bond at date 1.

Alternatively, the firm can raise two-period (long-term) debt. The corresponding contract requires the firm to pay back the principal at date 2 along with interest amounting to δ (also paid at date 2). This setup ensures that the firm is able to fully finance a project's operations between dates 1 and 2 using internal funds.[27] At both dates 1 and 2, positive cash flow remaining after paying any debt obligation can be distributed to shareholders (or re-invested at date 1 to finance operations). To simplify the analysis, we assume that the debt can only be paid off at date 1 if the project ceases operations, in which case the debt payoff is c. I.e., the firm cannot refinance long-term debt at date 1.[28]

Financing costs at date 0 are normalized to zero because the firm must pay this amount regardless of financing choice. Financing at date 1, however, is discretionary and assumed to carry a proportional cost of γ which can be viewed as the incremental cost of financing at date 1. Date 1 financing costs are paid at date 2 (i.e., they are funded by the lender).[29]

The firm management is assumed to maximize shareholder value. Importantly, long-term debt ensures the firm's ability to continue to operate the project between dates 1 and 2. As we next establish, this creates the possibility that the project will be operated in an inefficient way (i.e., when $\tilde{\mu} < c$). The root cause of this inefficiency is the non-contractibility of $\mathcal{I}_1$.[30] Because lenders will require compensation for this, short-term debt will always dominate long-term debt whenever $\gamma = 0$. In other words, the trade-offs between short- and long-term debt

[27]The quantity $\frac{\delta}{2}$ can be interpreted as a per-period coupon.

[28]In our setup, under costly refinancing, when long-term financing is preferred, the firm will also prefer to commit to non-callable long-term debt over callable long-term debt. This is because refinancing can only happen in good states when project continuation is efficient, so the refinancing costs cannot be offset against any efficiency gains.

[29]For simplicity, we assume away the possibility of financing c at date 0 using *both* short- and long-term debt. With such a choice, our analysis would remain qualitatively similar in the presence of sufficiently high fixed financing costs and/or long-term debt prepayment costs (both assumed to be zero in our setting).

[30]Note that, at date 1, $\tilde{\mu} < c$ reflects *expectations* of stakeholders over the profitability of a single project, so we are essentially assuming that stakeholders cannot contract on such future expectations. This echoes the large and important literature on incomplete contracts; see Hart (2017)'s Nobel Lecture published in the *American Economic Review*.

correspond to refinancing costs versus operational inefficiency.

Proposition 1. *In the absence of frictions other than the non-contractibility of $\mathcal{I}_1$, the following results characterize financing decisions of a senior debt obligation:*

i Under short-term debt financing at date-1, the project never operates in inefficient states, although in the absence of sufficient internal capital it may be prevented from operating in some efficient states by high costs of refinancing.

ii Under long-term debt financing, the firm will continue to operate its project at date 1 even when it is inefficient to do so.

iii If $v_1 + E[\tilde{\mu}] < 2c$ or $v_1 \geq 2c$ then financing with short-term debt is a (weakly) dominant strategy at date-0.

iv If $v_1 + E[\tilde{\mu}] \geq 2c$ and $v_1 < 2c$ then short-term debt weakly dominates long-term debt if and only if

$$E\Big[\big\{K - (\tilde{\mu} - c)\big\}^+\Big] - K \geq 0, \tag{1}$$

where $K = \gamma(2c - v_1)^+$ is the cost of short-term financing at date 1.

PROOF:

First we show that short-term financing is only employed efficiently (i.e., the firm refinances only in date 1 states where $\tilde{\mu} \geq c$). Consider that the firm has $v_1 - c$ to distribute and invest after paying off the first-period short-term debt. If a lender provides $\hat{c}$ for the project at date-1, in the absence of other frictions (like taxes), the present value of the firm's enterprise cash flow equals the present value of debt and equity:

$$\tilde{\mu} = \hat{c}(1 + \gamma) + \mathcal{E}_1,$$

where $\mathcal{E}_1$ is the present value of equity cash flow from continuing to operate the firm (and recall that $\tilde{\mu} = E[\tilde{v}_2 \mid \mathcal{I}_1]$). Consider that equity investment at date-1, $c - \hat{c}$, requires that $\mathcal{E}_1 \geq c - \hat{c}$. Substituting into the above equation results in

$$\tilde{\mu} = \hat{c}(1 + \gamma) + \mathcal{E}_1 \geq c + \gamma\hat{c}.$$

It should be clear that, to minimize financing costs, the firm will use as much internal capital as possible to continue a lucrative project at date-1. This sets

$\hat{c} = (2c - v_1)^+$ and the condition for continuing firm operations at date 1 is

$$\tilde{\mu} \geq c + \gamma(2c - v_1)^+.$$

In particular, the firm will never continue the project in inefficient states — those for which the present value of continuation is less than the cost of continuation: $\tilde{\mu} < c$. Refinancing costs may, however, lead the firm to cease operations in otherwise efficient states. I.e., when $c \leq \tilde{\mu} \leq c + \gamma(2c - v_1)^+$.

Consider, now, long-term debt. Because $v_1 \geq c$, the firm has enough internal capital to continue the project without raising new capital. In this case, managers can and will continue to operate the firm even if $\tilde{\mu} < c$ (i.e., financing operations is inefficient). This is because the alternative is to pay off the debt and end/liquidate the project. The latter payoffs are $v_1 - c$ and are dominated by $v_1 - c + E[\{\tilde{v}_2 - c - \delta\}^+ \mid \mathcal{I}_1]$, which is the sum of date-1 net cash flow (after investment) and the present value of the equity stake from continuing to operate the firm. In other words, in the presence of long-term financing, the firm will continue to operate even when it is inefficient to do so.

To establish part (iii) of the Proposition, consider that the first condition, $v_1 + E[\tilde{\mu}] < 2c$, implies that a commitment to operate the project through both periods has negative net present value of cash flow. Because $v_1 \geq c$, a short-term financing strategy has non-negative present value and is therefore weakly dominant because the firm can cease operations after date 1. The condition, $v_1 \geq 2c$ in part (iii), implies that the firm will have sufficient internal capital to continue project operations after date 1 under a short-term financing strategy. In this case, the firm experiences no refinancing costs and the difference between short- and long-term financing is that under the latter the firm always operates inefficiently. At date 0 the inefficiency costs of long-term debt accrue to the shareholders (because the fair value of any date 0 debt financing is fixed at c), meaning that short-term debt is weakly dominating.

To derive part (iv) of the proposition note that, as perceived at date 0, the value of the project's equity under short-term financing, $\mathcal{E}_{ST}$, is

$$\begin{aligned}\mathcal{E}_{ST} = & \overbrace{v_1 - c}^{\text{Profits from first period operations}} \\ & + E\Big[\overbrace{(\tilde{\mu} - c)\mathbf{1}_{c+\gamma(2c-v_1)^+\leq\tilde{\mu}}}^{\text{Profits from second period operations}}\Big] - E\Big[\overbrace{\gamma(2c - v_1)^+\mathbf{1}_{c+\gamma(2c-v_1)^+\leq\tilde{\mu}}}^{\text{Cost of date 1 refinancing}}\Big],\end{aligned}$$

where $\mathbf{1}_X$ is an indicator variable (equal to one if X is true and zero otherwise). Because long-term debt amounts to a commitment to operate in all states, the value of the firm's equity under this strategy at date 0 is simply,

$$\mathcal{E}_{LT} = \overbrace{v_1 - c}^{\text{Profits from first period operations}} + E\Big[\overbrace{\tilde{\mu} - c}^{\text{Profits from second period operations}}\Big]$$

Short-term debt weakly dominates long-term debt if and only if $\mathcal{E}_{ST} - \mathcal{E}_{LT} \geq 0$. Subtracting the two expressions yields

$$E\Big[\overbrace{(c - \tilde{\mu})\mathbf{1}_{\tilde{\mu}<c+\gamma(2c-v_1)^+}}^{\text{Relative cost of inefficient operations}}\Big] \geq E\Big[\overbrace{\gamma(2c - v_1)^+\mathbf{1}_{c+\gamma(2c-v_1)^+\leq\tilde{\mu}}}^{\text{Cost of short-term refinancing}}\Big].$$

Inequality (1) can be derived from the above by adding $E\Big[\gamma(2c-v_1)^+\mathbf{1}_{\tilde{\mu}<c+\gamma(2c-v_1)^+}\Big]$ to both sides.

□

Preference between short- and long-term debt comes down to which is less inefficient. The inefficiency of short-term debt comes from two sources: Financing costs in refinancing date-1 states and foregone profits from ceasing operations in efficient date 1 states because financing costs are prohibitive. The inefficiency of long-term debt arises from operating the project in *all* inefficient date 1 states. Inequality (1) requires balancing off the relative inefficiency of long-term debt from operating in inefficient date 1 states against the costs of refinancing short-term debt. In particular, we note that there is no inefficiency whenever the firm has sufficient internal capital at date 1 to finance date 2 operations (i.e., when $v_1 \geq 2c$) and short-term debt always (weakly) dominates in such instances.

It is worth noting that there is no under-investment in our stylized model. This differentiates our key mechanism from the one originally identified by Myers

(1977). In our setting, the driving friction is akin to asset substitution à la Jensen and Meckling (1976) because, in certain states, efficient liquidation is replaced by inefficient operation of the project.

Inequality (1) has a simple and intuitive interpretation. The quantity $\tilde{\mu} - c$ is the expected firm profitability from operations at date 1. The expression, $E\left[\left\{K-(\tilde{\mu}-c)\right\}^+\right]$ is therefore the date 0 option value of ceasing firm operations at date 1 should profitability fall below $K = \gamma(2c - v_1)^+$, the cost of short-term financing. This is the trigger level for liquidating the project under short-term debt, so one can also interpret $E\left[\left\{K-(\tilde{\mu}-c)\right\}^+\right]$ as the value of a put option that insures the firm stakeholders against the relative inefficiencies of long-term debt. The term subtracted from the value of this put option, K is the transaction cost of refinancing short term debt at date 1. Putting it all together, short-term debt financing is preferred at date 0 if the implied put option of avoiding long-term debt inefficiencies is more valuable than the transaction costs that come with short-term debt.

The payoff diagram associated with the put option analogy is depicted in Figure 3.[31] It is evident from the payoff diagram and inequality (1) that short-term debt dominates absent transaction costs (i.e., when $\gamma = 0$). That is because the inefficiency insurance created by short-term debt is free. More broadly, as viewed at date 0 (when the financing choice is made), if the distribution of expected profits at date 1 is mostly above K, then the net option value afforded by short-term debt is negative and the firm is best served by long-term debt. This is more likely to be case when one is predicting economic expansion at date 1. If, on the other hand, the distribution of expected profits at date 1 has significant mass at profitability below K, then the option created through financing with short-term debt is valuable on a net basis. This is more likely to be case when one is predicting economic recession at date 1. Flannery (1986) discusses a similar trade-off where inefficiency arises from asymmetric information (the firm's managers know $\tilde{\mu}$ at date 0), and short-term debt insures lenders against their inferior information. In the presence of financing costs at date 1, short-term debt may be used as a costly signal of a firm's higher quality. The opposite is true in our setting: Firms with better profit prospects opt for long-term debt. This feature of our model offers a

[31] Adding liquidation costs at date 1 acts to shift the payoff diagram to the left and tips the balance towards long-term debt.

more direct explanation of the empirical facts investigated in Section I.[32]

A. Overlapping generations extension

The preceding analysis provides a basic motivation for a mechanism that could potentially explain the empirical results in Section I: Firms shift to short-term project financing in anticipation of poor profitability states. We now extend the setting beyond a single project to study aggregate dynamics of financing choices and their relationship to aggregate growth. This will also allow for a comparison with the predictive power of aggregate default spreads on newly issued long-maturity bonds.

In the extended model, new two-period projects requiring debt financing, each similar to the one analyzed above, enter at every date. Let $v_{s,t}$ and $v_{l,t}$ denote the number of newly started projects at date t that are initially financed using short-term and long-term debt financing, respectively. At date t there will also be some "vintage projects" — those projects that started at date $t-1$. Although all vintage projects at date t exit prior to date $t+1$, some exit at the beginning of the period (i.e., are liquidated) while others continue operations through the end of the period. From Proposition 1, all vintage projects initially financed using long-term debt are continued, but some that were initially financed using short-term debt might be liquidated rather than continued. Denote by ℓ_t the fraction of the $v_{s,t-1}$ vintage projects previously financed using short-term debt that are liquidated rather than continued at date t. Let ρ_t denote the number of remaining vintage projects (those that are continued at date t). Define $\phi_{s,t}$ to be the fraction of newly entering projects at date t that are financed with short term-debt. To maintain stationarity, we assume that the mass of projects is constant through time and normalized to one. This requires that all exiting projects are immediately recycled as entering projects. From these assumptions

[32] Diamond (1991) also relies on asymmetric information as a key friction in modeling firm debt maturity choice. In an enriched setting relative to Flannery (1986), it is possible that short-term debt is chosen by the best as well as the worst firms (i.e., the debt maturity choice is not monotonic in firm quality). Although it is outside the scope of our current investigation, it would be valuable to attempt to empirically attribute firm debt maturity choices to the different trade-offs considered in the theoretical literature.

we derive the following evolution equations for the economy.

$$\begin{aligned}
\rho_t &= v_{l,t-1} + (1-\ell_t)v_{s,t-1} \\
v_{s,t} &= \phi_{s,t}(\rho_{t-1} + \ell_t v_{s,t-1}) \\
v_{l,t} &= (1-\phi_{s,t})(\rho_{t-1} + \ell_t v_{s,t-1}) \\
1 &= \rho_t + v_{s,t} + v_{l,t}.
\end{aligned}$$

The first equation expresses that continuing vintage projects at date t include all projects that entered at $t-1$ save for those that are liquidated at date t. The second equation is derived through the following logic. First note that the number of exiting and entering projects at date t is equal. The former equals all continued vintage projects from date $t-1$ (i.e., ρ_{t-1}) plus projects that entered at $t-1$ but must now be liquidated for lack of financing (i.e., $\ell_t v_{s,t-1}$)). Finally, $v_{s,t}$ is, by definition, equal to $\phi_{s,t}$ times the number of newly entering projects ($v_{l,t}$ is similarly derived). The last equation states that the total number of projects, continuing vintage and newly entered, is equal to one.

Both $\phi_{s,t}$ and ℓ_t are functions of current economic conditions and the distribution of firm characteristics, and will be shortly pinned down by further assumptions. Given a time series of $\phi_{s,t}$ and ℓ_t, it should be clear that $v_{l,t}$ is redundant. By employing the stationarity condition, the evolution can be reduced to

$$\rho_t = 1 - \rho_{t-1} - \ell_t v_{s,t-1} \tag{2}$$

$$v_{s,t} = \phi_{s,t}(1-\rho_t). \tag{3}$$

The total number of projects issuing new debt at date t is $v_{s,t}+v_{l,t}+(1-\ell_t)v_{s,t-1}$. The first term corresponds to newly entering projects while the third reflects the refinancing of vintage projects. The proportion of short-term debt issued relative to total debt issued at date t is given by

$$f_{s,t} = \frac{v_{s,t} + (1-\ell_t)v_{s,t-1}}{v_{s,t} + v_{l,t} + (1-\ell_t)v_{s,t-1}}. \tag{4}$$

This is the main quantity of interest that we investigate.[33]

To derive $\phi_{s,t}$, we first note that it can only differ from 0 or 1 if profit expec-

[33] Using the stationarity condition together with Equation (2), the denominator in (4) can be expressed as $\rho_{t-1} + v_{s,t-1}$.

tations are heterogeneous across projects (otherwise, all projects would receive the same type of financing at entry). Recall that for each project entering at date t and indexed by i, current period profits are $v_{1,i} - c_i > 0$ and expected profitability from continuing operations past date $t+1$, i.e., $\tilde{\mu}_i - c_i$, is a random variable that is realized at date $t+1$. Assume that $\tilde{\mu}_i - c_i = \mu_i - c_i + \sigma_\mu \tilde{n}_i$ where $\mu_i - c_i \geq 0$ and $\tilde{n}_i$ is a standard Normal random variable.[34] Suppose, further, that the unconditional project expected profit, $\mu_i - c_i$, is log-normally distributed across other entering projects with aggregate (cross-sectional) mean of expected profits $p_{C,t}$, assumed to be log-affine in GDP growth. The cross-sectional variance of log $\mu_i - c_i$ across projects is σ_C^2 and constant through time.

Based on the assumptions above, and from Proposition 1, a project is initially financed using short-term debt upon entry if and only if

$$E[(\hat{\gamma} + c_i - \mu_i - \sigma_\mu \tilde{n}_i)^+] \geq \hat{\gamma},$$

where, for simplicity, $\hat{\gamma} = \gamma_i (2c_i - v_{1,i})^+ > 0$ is assumed constant across projects. The corresponding analytic condition for initial financing using short-term debt is

$$\frac{\hat{\gamma} + c_i - \mu_i}{\sigma_\mu} N\big(\frac{\hat{\gamma} + c_i - \mu_i}{\sigma_\mu}\big) + \frac{1}{\sqrt{2\pi}} \exp\big(\frac{\hat{\gamma} + c_i - \mu_i}{\sigma_\mu}\big) \geq \frac{\hat{\gamma}}{\sigma_\mu},$$

where $N(\cdot)$ is the cumulative normal distribution. Define m^* to be the largest value of $\mu_i - c_i$ for which the inequality holds. I.e., all newly entering projects with $\mu_i - c_i \leq m^*$ finance with short-term debt. If entering projects form a continuum, the log-normal cross-sectional distribution assumption implies that

$$\phi_{s,t} = N\Big(\frac{\ln \frac{m^*}{p_{C,t}}}{\sigma_C} + \frac{\sigma_C}{2}\Big). \tag{5}$$

Note that m^* only depends on σ_μ and $\hat{\gamma}$, and is time-independent under our assumptions. Thus $\phi_{s,t}$ is monotonically decreasing in aggregate expected profitability, $p_{C,t}$, and therefore in expected GDP growth.

Turning attention to calculating ℓ_t, a new project with $\mu_i - c_i \leq m^*$ will be initially financed with short-term debt and has a chance of $N\big(\frac{\hat{\gamma}+c_i-\mu_i}{\sigma_\mu}\big)$ of negative continuation value (and, therefore, liquidation) at the beginning of its second period. Assuming that $\tilde{n}_i$ is independent across projects and averaging over the

[34]For simplicity, we assume that σ_μ^2 is constant across projects and time.

continuum of log-normally distributed projects yields

$$\ell_t = \frac{1}{\phi_{s,t}} \int_0^{m^*} N\big(\frac{-p + \hat{\gamma}}{\sigma_\mu}\big) dF_{LN}(p; p_{C,t}, \sigma_C), \tag{6}$$

where $F_{LN}(p; p_{C,t}, \sigma_C)$ is the log-normal cumulative distribution function with mean $p_{C,t}$ and log-variance σ_C^2. Once a specification of $p_{C,t}$ and its dependence on GDP growth is provided, equations (2)-(6) encode all the information needed to fully describe the evolution of $f_{s,t}$ and its relationship with GDP.

Consider, now, the default premium corresponding to the yield spread on newly issued long-maturity bonds. For an individual project, indexed by i, the default premium, δ_i, is determined by the condition that project expected value from operating in its second year less the amount financed should equal the residual equity in the project. Specifically,

$$\mu_i - c_i = E\big[(\tilde{v}_{i,2} - c_i - \delta_i)^+\big].$$

The project revenues, $\tilde{v}_{i,2}$, consist of the conditional mean known after the first period, $\tilde{\mu}_i$, and some unexpected "shock" about the conditional mean, which we denote as $\tilde{\epsilon}_i$ — this shock corresponds to the actual realization of profit outcomes at date 2 of the project's life. If $\tilde{\epsilon}_i$ is normally distributed with variance $\sigma_{\epsilon,t}^2$ then δ_i solves

$$\frac{\mu_i - c_i}{\sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}} = \frac{\mu_i - c_i - \delta_i}{\sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}} N\big(\frac{\mu_i - c_i - \delta_i}{\sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}}\big) + \frac{1}{\sqrt{2\pi}} \exp\big(\frac{\mu_i - c_i - \delta_i}{\sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}}\big). \tag{7}$$

The solution takes the form $\delta_i = \sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}\, \hat{\delta}\big(\frac{\mu_i - c_i}{\sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}}\big)$ where $\hat{\delta}(x)$ is decreasing in x.[35] From this, one sees that δ_i is decreasing in project profitability, $\mu_i - c_i$, and increasing in total cash flow uncertainty, $\sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}$. Aggregating across all

[35] $\hat{\delta}(x)$ is the solution to $x = (x - \hat{\delta})N(x - \hat{\delta}) + \frac{1}{\sqrt{2\pi}} \exp\big(-\frac{1}{2}(x - \hat{\delta})^2\big)$. For $\hat{\delta}$ to be well-defined, it must be that $x > 0$. This is almost surely guaranteed by the assumption that $\mu_i - c_i$ is log-normally distributed across projects.

firms that finance using long-term debt at date t leads to

$$\text{Def}_t = \frac{\sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}}{1-\phi_{s,t}} \int_{m^*}^{\infty} \hat{\delta}\Big(\frac{p}{\sqrt{\sigma_\mu^2 + \sigma_{\epsilon,t}^2}}\Big) dF_{LN}(p; p_{C,t}, \sigma_C). \tag{8}$$

It is important to emphasize that the outcome variance component, $\sigma_{\epsilon,t}^2$, in (7) plays no role in the initial financing decision. This hints at differences between the time-series predictive power of aggregate financing choices and aggregate default premia. It is to highlight this key differentiation that we explicitly consider time variation in $\sigma_{\epsilon,t}^2$.

Time-invariant setting

It is instructive to first illustrate the model implications when $\phi_{s,t}$ and ℓ_t are time-invariant. In this case, there is a unique time-invariant solution for Equations (2)-(4) given by

$$\begin{aligned} \rho &= (1-\phi_s\ell)/(2-\phi_s\ell) \\ v_s &= \phi_s/(2-\phi_s\ell) \\ f_s &= \frac{\phi_s + (1-\ell)\phi_s}{1+(1-\ell)\phi_s}. \end{aligned}$$

If projects' expected profitability is weakly increasing in GDP growth expectations then, from part (iv) of Proposition 1, ϕ_s, should decrease with GDP growth expectations. Likewise, projects' liquidation rate should also be decreasing in GDP growth expectations. From this, it should be clear that the fraction of new short-term debt financing each period, v_s, is monotonically decreasing in GDP growth expectations.

The top plot in Figure 4 depicts f_s, the proportion of short-term debt issuance, as a function of p_C. We set the project financing cost to $c_i = 1$ for all firms, the issuance costs to $\hat{\gamma} = 0.005$, uncertainty in expected profits to $\sigma_\mu = 0.05$, and the cross-sectional standard deviation of expected profits, σ_C, to 0.05. The parameters are chosen to crudely reflect the cross-section of U.S. firms. For $p_C \approx 4.5\%$, the fraction of projects financed using short-term debt roughly matches the empirical unconditional average of 40% seen in Figure 1. The plot illustrates the negative monotonic relationship between aggregate profitability and aggregate financing decisions. In particular, time-invariant economies characterized by aggregate profitability that are only a few percentage points apart exhibit markedly different aggregate financing decisions. We will shortly demonstrate that this sensitivity translates into strong predictive power that $f_{s,t}$ has for aggregate growth in a dynamic setting.

The bottom plot in Figure 4 depicts the aggregate default premia against p_C for several values of σ_ϵ^2 in the time-invariant case (using the same parameters employed in the top plot).[36] While the default premia also decreases with p_C, it is also quite sensitive to aggregate profit volatility.

Adding simple dynamics

To introduce time-varying dynamics into the model described by Equations (2) and (3) we depart from the assumption that aggregate expected profits, p_C, are constant. Instead, we assume that $p_{C,t}$ imperfectly anticipates shocks to GDP growth. Specifically assume that GDP growth shock at date $t+1$, $\tilde{\varepsilon}_{\text{GDP},t+1}$ is Gaussian and iid, and that average expected aggregate profits at date t are given by

$$p_{C,t} = p_C \exp\left(s_p(\zeta_p \tilde{\varepsilon}_{\text{GDP},t+1} + \sqrt{1-\zeta_p^2}\tilde{\varepsilon}_{p\text{-noise},t}) - \frac{s_p^2}{2}\right),$$

where $\tilde{\varepsilon}_{p\text{-noise},t}$ is iid "noise" effectively screening future GDP outcomes, p_C is the unconditional mean of $p_{C,t}$, s_p^2 is the log-variability of aggregate profit, and ζ_p is a measure of the correlation between aggregate expected profitability and future GDP growth. We stress that $p_{C,t}$, representing aggregate profit *expectations*, is not assumed to be directly observed. What is observed by all are prices set by investors (e.g., default premia) and the decisions made by firms and lenders (project financing choices). The stakeholders of a new project i at date t observe $\mu_{i,t}$, which is drawn from a distribution that is centered around $p_{C,t}$. This means that, absent the ability to aggregate information, $p_{C,t}$ is unobservable and can only be viewed as a common latent factor influencing expectations over individual project profits. It is by aggregating over firm maturity choices to arrive at $f_{s,t}$ that $p_{C,t}$ becomes observable and its information content for forecasting future GDP can be exploited.

[36]Values chosen for σ_ϵ^2 are based on firm-level ratios of EBITDA to revenues plus total assets. The average firm-level ratio of this profitability ratio is 3.5%.

To model the dynamics of the aggregate default premium we assume that profit realization volatility, $\sigma_{\epsilon,t}$, also varies *inversely* with GDP shocks — in other words, we allow for the possibility that recessions can be associated with both low expected profitability *and* greater outcome variance.[37] This is done in a similar manner to our modeling of $p_{C,t}$:

$$\sigma_{\epsilon,t} = \sigma_\epsilon \exp\left(s_\epsilon(\zeta_\epsilon \tilde{\varepsilon}_{\text{GDP},t+1} + \sqrt{1-\zeta_\epsilon^2}\tilde{\varepsilon}_{\epsilon\text{-noise},t}) - \frac{s_\epsilon^2}{2}\right),$$

where we expect to set $\zeta_\epsilon < 0$. We retain the remaining constant model parameters from the time-invariant exercise in Figure 4 and fix $E[p_{C,t}] = 0.045$, $\text{StDev}[p_{C,t}] = 0.035$, and $E[\sigma_{\epsilon,t}] = 0.035$. For a given choice of ζ_p, ζ_ϵ and s_ϵ, we simulate 900 time-series panels of the three basic shocks $\tilde{\varepsilon}_{\text{GDP},t}$, $\tilde{\varepsilon}_{p\text{-noise},t}$, and $\tilde{\varepsilon}_{\epsilon\text{-noise},t}$. Each panel simulation is initialized with ρ_0, the initial mass of vintage projects, set to 0.5, and for a time-series length of 130 periods. Only the last 30 periods are retained, allowing the panel to be essentially independent of the initialization choice.[38]

For each panel, we solve for the time series of $\phi_{s,t}$, ℓ_t and DEF_t. These, in turn, are used to solve Equations (2)-(4). The result is a panel of time-varying short-term issuance shares, $f_{s,t}$, and default premia, DEF_t, both of which anticipate future GDP shocks, $\tilde{\varepsilon}_{\text{GDP},t+1}$. Plots in the left column of Figure 5 depict pooled simulated panel correlations between $f_{s,t}$ and DEF_t as well as pooled predictive regression statistics from regressing $\tilde{\varepsilon}_{\text{GDP},t+1}$ on $f_{s,t}$ and DEF_t. In each graph ζ_p is varied from 0 to 1. Each plot contains two graphed lines, one in which $\zeta_\epsilon = 0$ and one in which $\zeta_\epsilon = 1$. As documented in the "Related Literature" section of the Introduction, maturity choice models of asymmetric information predict a different, potentially opposite and even non-monotonic, relationship between maturity and firm quality. To address the possibility that, in practice, our model assumptions are unlikely to account for all sources of influence affecting financing

[37] There may be other ways to introduce predictive information in default spreads that is orthogonal to that in maturity choices. The former could, for instance, depend on counter-cyclical aggregate risk aversion (as would be the case in a "habit formation" model). There may be some empirical validity for this given that the EBP measure of Gilchrist and Zakrajšek (2012) captures risk premia associated with bonds that may not be associated with volatility of outcomes. Because our model features risk-neutral stakeholders, time-varying volatility rather than risk tolerance is a more appropriate channel for us to explore.

[38] The choice of 30 periods in the time series is meant to roughly capture the span covered by the data. It also serves to illustrate how the empirical results can arise from a data set with relatively few independent observations.

decisions and default premia, we consider the effect of adding observation noise to $f_{s,t}$ and DEF_t. The plots in the right column of Figure 5 are generated by adding such observation noise. The noise added to each of $f_{s,t}$ and DEF_t in the right column plots is iid, normally distributed, and equal in variance to the variance of the original (i.e., the observation noise accounts for half of the variance of each of $f_{s,t}$ and DEF_t).

To clarify what the plot conveys, consider, for instance, the case in which $\zeta_p = 0.5$, $\zeta_\epsilon = 0$, and no observation noise is added to $f_{s,t}$ and DEF_t. The 30-period correlation between the two predictor variables, pooled across 900 simulated panels, is 0.63, which is much too high relative to the observed correlations between f_{sl} and spread-based predictors (see Table 2). The pooled adjusted R^2 of regressing simulated GDP on the two predictive variables is about 0.23, which is on the low side but roughly consistent with the incremental adjusted R^2 captured by maturity and spread variables in Tables 3 and 4. Finally, while the pooled t-statistic for $f_{s,t}$ suggests predictive significance (and the correct sign), DEF_t makes no significant contribution to predicting GDP beyond the information contained in $f_{s,t}$.[39] This suggests that the parameter choice doesn't adequately reflect the observed statistics.

Surveying the eight plots leads to several insights. Firstly, observation noise appears to be important to reduce the correlation between $f_{s,t}$ and DEF_t to a level consistent with stylized facts. Though it may come as no surprise, this suggests that our model only partially explains the rationale for bond maturity choice. With the inclusion of such noise, one needs ζ_p to range between 0.4 and 0.9 to achieve an adjusted R^2 between 0.3 and 0.4 in the predictive regression. Finally, for DEF_t to significantly contribute to the predictive regression in the presence of $f_{s,t}$, ζ_ϵ cannot be negligible. In other words, the model suggests the predictive power of $f_{s,t}$ for GDP arises from anticipation of future profitability while the *complementary* predictive power of ζ_ϵ for GDP comes from anticipating a larger variance of outcomes.

Using the plots as a guide, one can arrive at a set of parameters that appear broadly consistent with our empirical analysis. For example, setting $\zeta_p = 0.8$, $\zeta_\epsilon = -0.55$ and adding observation noise to $f_{s,t}$ and DEF_t results in a pairwise correlation of 0.35 between the predictive variables and a predictive regressions

[39] As is evident from Equation (8) and Figure 4, DEF_t is a significant predictor of simulated GDP on its own.

with adjusted R^2 of 0.37 and t-statistics of -2.37 and -2.30 for $f_{s,t}$ and DEF_t, respectively (i.e., the spread and maturity choice variables contribute roughly equally).

B. Model takeaways and additional thoughts

The model examines how the anticipation of future profits is incorporated into the maturity choice decision. Long maturity debt is more expensive because it incentivizes inefficient firm operations in low expected profitability states. Short maturity financing is preferred when the future costs of refinancing are low, in present value terms, relative to the inefficiency of long-maturity debt. Because the trade-off is based on profit expectations, aggregate financing choices reflect aggregate expectations of profitability, and therefore GDP growth. Viewed from this perspective, it is sensible that aggregate financing choices would predict future GDP growth.

What is less clear is why the information content in aggregate financing choices is not subsumed in aggregate yield spreads on long-maturity bonds. In the model, aggregate maturity choice is highly sensitive to future profit expectations but not sensitive to realized profit volatility. This is because realized profit volatility is unrelated to firm decisions to operate inefficiently. By contrast, aggregate yield spread is sensitive to both, but less sensitive to profit expectations than aggregate maturity choice. The lower sensitivity arises because, when profitability declines, projects with poor profit expectations meriting high yield spreads are instead financed using short-term debt.

Thus, if realized profit volatility is unrelated to changes in GDP growth, aggregate maturity choice would be a better predictor than aggregate yield spreads. If, on the other hand, realized profit volatility is negatively related to changes in GDP growth, then aggregate yield spreads become as sensitive (or more) to GDP growth as aggregate maturity choice. The main point is that the two variables can be complementary GDP growth predictors because their respective sensitivities to GDP growth arise through distinct channels.

A final puzzle to ponder is why a value-weighted average of aggregate maturity choice would be less sensitive to to GDP growth than $f_{s,t}$, which is an arithmetic average. To understand this, consider that larger firms are also firms with more profitable projects.[40] The model predicts that more long-term financing is optimal for more profitable projects. Thus value-weighting maturity choice will result in a measure that is less sensitive to GDP growth because the most valuable projects will receive long-term financing regardless of the state of the economy. This will be exacerbated by the introduction of observation noise: If half of the variation in $f_{s,t}$ arises from changes in anticipated aggregate profitability and the remainder from observation noise, then value weighting will further reduce the signal value of v_{sl} of future aggregate profitability.

III. Conclusions

We empirically demonstrate that corporate bond maturity decisions contain valuable information about future aggregate growth and the business cycle. The quarterly tabulated number of issued short-term (5 years maturity or less) rated corporate bonds relative to their long-maturity (10 years maturity or more) counterparts is a strong predictor of future real GDP growth. The measure's forecasting power for GDP growth is impressive, capturing nearly half of the total forecasting power in a univariate forecasting regression as compared to a multivariate regression that includes a collection of known growth predictors. Within a multivariate setting, the aggregate maturity choice variable retains a level of predictive significance (economic and statistical) that ranks near the top of other growth predictive variables. This suggests that our new measure contains information about future aggregate growth that is not reflected by other variables explored in the large literature on forecasting the business cycle.

Corporate bond maturity choices can contain new information about future aggregate growth if each issuing firm's decision conveys a signal of its stakeholders' views on future economic prospects. Aggregating individual signals, even if each is weak, can lead to a measure that predicts future GDP. So explaining the informational content of our new measure reduces to explaining how forecasts of future economic outcomes relate to current financing decisions. To do that, we turn to the rich literature on firm financing choices.

It is well-recognized in the corporate finance literature that financing using short term debt can solve future conflicts between long-term debt holders and

[40] In present value terms, this is nearly tautological — a more profitable project has a higher present value than an unprofitable project, everything else being equal. More broadly, however, survival bias can drive a relationship between size and profitability (Luttmer, 2007).

shareholders. The source of such conflicts is the different stake that lenders and shareholders have in the enterprise at different economic states: Shareholders receive the lion's share of enterprise value in high cash flow states but have little stake left in poor firm performance states. This can lead to a situation where firm managers adopt a negative NPV strategy, benefiting shareholders yet reducing overall enterprise value and, therefore, harming other stakeholders (e.g., lenders). Building on this, we develop a theoretical model arguing that firms are more likely to finance using short maturity debt when they and their lenders anticipate that future firm profit forecasts will be low, requiring a downward adjustment in firm investment strategy (e.g., the discontinuation of unprofitable operations) to maximize enterprise value. Unless managers can commit to always maximize enterprise value, financing using long-term debt can result in a situation where shareholders benefit at the expense of pre-existing lenders from a failure to adjust to future negative news by, say, continuing to invest in a project that has negative NPV. This "overinvestment" problem reduces expectations of future enterprise cash flow and shareholders must bear the associated devaluation when seeking initial financing.

The tilt towards short-term financing in the preceding agency problem must be balanced against additional costs of refinancing. We show that short-term financing is tantamount to a costly commitment option — acquiring this option is "cheap" if refinancing costs are low and/or managers anticipate substantial risk that low future profit forecasts will lead to a conflict of interest between lenders and shareholders. Correspondingly, a firm's decision to use short-term over long-term financing (weakly) signals pessimism about the direction of the economy. This signal, on its own, may be far too noisy to meaningfully exploit because some firms are profitable even during recessions (e.g., pharmaceuticals) while others may be expected to be unprofitable during an expansion (e.g., so-called big-box retailers during the economic expansion that started after the Great Financial Crisis). However, when aggregated across all bond issuing firms, weak but imperfectly correlated signals about future economic activity can contain a significant amount of information.

We confirm the intuition outlined above within a dynamic overlapping generations model of finitely-lived heterogeneous firm projects, each requiring financing that can be long-term or rolled over (short-term). At initial financing, firm stakeholders (managers and lenders) receive information about future expected profits (on which future project continuation decisions will be made). This information has a component that is common across firms and correlated with future realizations of GDP. Simulations demonstrate that aggregate maturity choice is indeed a good predictor of GDP — even better than the model's aggregated default premia on long-maturity bonds. The latter's (but not the former's) predictive power is boosted if a firm's future profit volatility measure depends inversely on the future economic state (i.e., average profit realization volatility is higher in recessionary states). This is because aggregate maturity conveys information about *future profit expectations* better than aggregate yields, but aggregate yields better convey information about *future profit volatility.* As long as the overall economic conditions impact both expectations and volatility, the two measure can be shown to be complementary in forecasting GDP.

Our empirical findings contribute to an important and large literature on forecasting the business cycle. Our theoretical model and corresponding analysis help to provide a microfoundation through which the empirical findings can be understood.

Table 1: Summary statistics for variables used in the predictive regression of real gdp growth. The treasury term spread, federal funds rate, consumer price index (CPI) growth, real GDP growth, the Moody's BAA-AAA credit spread, and the NFCI index are obtained from FRED (St. Louis Federal Reserve Bank). Data on corporate debt issuance, used to calculate f_sl, v_sl, and the Greenwood and Hanson (2013) measure of high-yield bond issuance (LnHYShare), are obtained from Mergent FISD via WRDS. Data on the GZ spread and excess bond premium (EBP), developed in Gilchrist and Zakrajšek (2012), are obtained from the Federal Reserve. MDUR is a measure of prevailing government treasury duration as developed by Greenwood, Hanson and Stein (2010) in their gap-filling theory of corporate maturity choice (and calculated from CRSP and WRDS data). The quarterly data sample starts at 1982Q2 and ends at 2020Q1. This is the maximal window during which all variables are available.

	Mean	Median	SD	p1	p99
Term spread	0.018	0.018	0.011	-0.0043	0.038
Fed funds rate	0.041	0.042	0.032	0.00080	0.11
CPI growth	0.0066	0.0067	0.0059	-0.0052	0.024
GDP growth	0.0069	0.0072	0.0060	-0.012	0.021
BAA-AAA spread	0.010	0.0092	0.0043	0.0055	0.029
LnHYShare	-1.96	-1.76	0.88	-5.26	-0.79
GZ	1.98	1.72	0.96	0.84	6.36
EBP	0.086	-0.011	0.57	-0.70	2.66
NFCI	-0.27	-0.46	0.64	-0.98	2.89
MDUR	2138.9	2022.5	395.2	1567.2	3057.5
f_{sl}	1.06	0.82	0.93	0.077	5.74
v_{sl}	0.69	0.57	0.59	0.016	3.24

Table 2: Correlation matrix of f_{sl} and v_{sl} with the key macro-predictive variables discussed in recent literature and, like the LnHYShare measure of Greenwood and Hanson (2013), are calculated from Mergent FISD data. Data on the GZ spread and excess bond premium (EBP), developed in Gilchrist and Zakrajšek (2012), are obtained from the Federal Reserve. MDUR is a measure of prevailing government treasury duration as developed by Greenwood, Hanson and Stein (2010) in their gap-filling theory of corporate maturity choice (and calculated from CRSP and WRDS data). The quarterly data sample starts at 1982Q2 and ends at 2020Q1. This is the maximal window during which all variables are available.

	f_sl	v_sl	LnHYShare	GZ	EBP	NFCI	MDUR
f_{sl}	1.00						
v_{sl}	0.55	1.00					
	(0.00)						
LnHYShare	-0.03	-0.25	1.00				
	(0.71)	(0.00)					
GZ	0.39	0.28	0.06	1.00			
	(0.00)	(0.00)	(0.47)				
EBP	0.24	0.26	-0.25	0.76	1.00		
	(0.00)	(0.00)	(0.00)	(0.00)			
NFCI	0.27	0.27	-0.29	0.43	0.62	1.00	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		
MDUR	-0.03	-0.07	0.09	0.17	-0.15	-0.26	1.00
	(0.69)	(0.41)	(0.26)	(0.03)	(0.07)	(0.00)	

Note: p-values in parentheses

Table 3: Regression results for $g_{t+1} = \beta_0 + \beta' \cdot y_t + \varepsilon_{t+1}$, where g_{t+1} is real seasonally adjusted quarterly GDP growth and y_t is a vector of predictive variables (lagged one quarter). The list of explanatory variables varies across specifications (columns numbered 1-11). The treasury term spread, federal funds rate, consumer price index (CPI) growth, real GDP growth, the Moody's BAA-AAA credit spread, and the NFCI index are obtained from FRED (St. Louis Federal Reserve Bank). Data on corporate debt issuance, used to calculate f_sl, v_sl, and the Greenwood and Hanson (2013) measure of high-yield bond issuance (LnHYShare), are obtained from Mergent FISD via WRDS. Data on the GZ spread and excess bond premium (EBP), developed in Gilchrist and Zakrajšek (2012), are obtained from the Federal Reserve. The quarterly data sample starts at 1982Q2 and ends at 2020Q1. This is the maximal window during which all variables are available.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Term spread	0.105*	0.0593	0.110*	0.0610	0.110*	0.0651	0.0841	0.0941*	0.0432	0.0497	0.0662	0.0682
	(0.0504)	(0.0478)	(0.0495)	(0.0487)	(0.0493)	(0.0516)	(0.0495)	(0.0474)	(0.0473)	(0.0457)	(0.0450)	(0.0464)
Fed funds rate	0.173**	0.171**	0.186**	0.173**	0.220***	0.0719	0.189***	0.249***	0.159*	0.232***	0.272***	0.348***
	(0.0576)	(0.0536)	(0.0567)	(0.0541)	(0.0588)	(0.0679)	(0.0562)	(0.0566)	(0.0638)	(0.0532)	(0.0550)	(0.0883)
CPI growth	-0.112*	-0.135**	-0.125*	-0.136**	-0.0940	-0.115*	-0.118*	-0.0646	-0.113*	-0.120**	-0.0795	-0.0917
	(0.0511)	(0.0477)	(0.0503)	(0.0480)	(0.0504)	(0.0500)	(0.0497)	(0.0491)	(0.0463)	(0.0457)	(0.0468)	(0.0466)
BAA-AAA spread	-0.132*	-0.126*	-0.133*	-0.126*	-0.131*	-0.0271	-0.0362	0.113	-0.0538	-0.0505	0.0407	0.0568
	(0.0565)	(0.0526)	(0.0554)	(0.0527)	(0.0552)	(0.0678)	(0.0630)	(0.0757)	(0.0636)	(0.0573)	(0.0729)	(0.0761)
GDP growth	0.214***	0.163**	0.194***	0.163**	0.158**	0.169**	0.149**	0.153**	0.0724	0.0576	0.0747	0.0461
	(0.0539)	(0.0512)	(0.0533)	(0.0514)	(0.0564)	(0.0553)	(0.0564)	(0.0523)	(0.0550)	(0.0546)	(0.0523)	(0.0538)
f_{sl}		-0.215***		-0.210***					-0.191***	-0.208***	-0.172***	-0.188***
		(0.0442)		(0.0527)					(0.0456)	(0.0423)	(0.0446)	(0.0479)
v_{sl}			-0.118**	-0.0100								
			(0.0444)	(0.0503)								
LnHYShare					0.138**				0.164***	0.141**	0.142**	0.116*
					(0.0493)				(0.0459)	(0.0446)	(0.0442)	(0.0479)
GZ						-0.195**			-0.132			0.139
						(0.0725)			(0.0723)			(0.128)
EBP							-0.191**			-0.148**		-0.206*
							(0.0615)			(0.0563)		(0.0993)
NFCI								-0.343***			-0.233**	-0.215**
								(0.0754)			(0.0754)	(0.0773)
Adjusted R^2	0.242	0.345	0.272	0.340	0.276	0.273	0.285	0.332	0.396	0.410	0.420	0.434

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Stability of f_{sl} as a growth predictor. The table presents additional regression results to complement those in Table 3. The regression is $g_{t+1} = \beta_0 + \beta' \cdot y_t + \varepsilon_{t+1}$, where g_{t+1} is real seasonally adjusted quarterly GDP growth and y_t is a vector of predictive variables (lagged one quarter). Each specification (columns numbered 1-8) is intended to assess the predictive value of f_{sl} as an explanatory variable by progressively including other "control" variables. Only lagged GDP and growth predictors that have emerged in recent literature are included as controls.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
f_{sl}	-0.271***	-0.208***	-0.211***	-0.213***	-0.176***	-0.195***	-0.189***	-0.171***	-0.202***	-0.198***	-0.161***
	(0.0461)	(0.0444)	(0.0524)	(0.0437)	(0.0456)	(0.0440)	(0.0446)	(0.0440)	(0.0435)	(0.0443)	(0.0453)
GDP growth		0.227***	0.227***	0.196***	0.158**	0.167**	0.197***	0.0853	0.147**	0.176***	0.0836
		(0.0444)	(0.0445)	(0.0454)	(0.0522)	(0.0500)	(0.0460)	(0.0546)	(0.0502)	(0.0465)	(0.0548)
v_{sl}			0.00499								
			(0.0510)								
LnHYShare				0.109*				0.151***	0.0956*	0.0920*	0.155**
				(0.0437)				(0.0440)	(0.0436)	(0.0445)	(0.0497)
GZ					-0.132*			-0.186***			-0.214**
					(0.0544)			(0.0548)			(0.0799)
EBP						-0.121*			-0.106*		0.0582
						(0.0495)			(0.0494)		(0.0781)
NFCI							-0.100*			-0.0788	-0.0480
							(0.0459)			(0.0465)	(0.0536)
Adjusted R^2	0.183	0.301	0.296	0.325	0.324	0.324	0.318	0.370	0.341	0.333	0.365

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: The predictive value of treasury securities' duration for aggregate growth. The table presents regression results for $g_{t+1} = \beta_0 + \beta' \cdot y_t + \varepsilon_{t+1}$, where g_{t+1} is real seasonally adjusted quarterly GDP growth and y_t is a vector of predictive variables (lagged one quarter). Each specification (columns numbered 1-7) contains MDUR, a measure of prevailing government treasury duration as developed by Greenwood, Hanson and Stein (2010) in their gap-filling theory of corporate maturity choice (and calculated from CRSP and WRDS data). The purpose of the table is to assess the extent to which MDUR accounts for the explanatory power of f_{sl}, as might be conjectured based on the gap-filling theory.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Fwd GDP	Fwd GDP	Fwd GDP	Fwd GDP	Fwd GDP	f_{sl}	f_{sl}
Standardized values of (mdur)	-0.138**	-0.0895	-0.0337	-0.141	-0.0492	-0.115	-0.0856
	(0.0499)	(0.0459)	(0.0786)	(0.0751)	(0.0772)	(0.104)	(0.117)
GDP growth		0.269***	0.217***	0.173***	0.199***		
		(0.0459)	(0.0547)	(0.0510)	(0.0540)		
Term spread			0.0902	-0.00854	0.0882	-0.123	-0.0620
			(0.0616)	(0.0597)	(0.0603)	(0.0828)	(0.0929)
Fed funds rate			0.143	0.0443	0.142		
			(0.0915)	(0.0861)	(0.0895)		
CPI growth			-0.111*	-0.132**	-0.123*		
			(0.0514)	(0.0474)	(0.0505)		
BAA-AAA spread			-0.129*	-0.111*	-0.128*	-0.0468	-0.0481
			(0.0573)	(0.0527)	(0.0561)	(0.0628)	(0.0710)
f_{sl}				-0.239***			
				(0.0455)			
v_{sl}					-0.120**	0.371***	
					(0.0447)	(0.0583)	
L.f_{sl}						0.512***	0.657***
						(0.0702)	(0.0749)
DGS3MO						-0.0437	-0.0238
						(0.0370)	(0.0417)
Adjusted R^2	0.043	0.218	0.238	0.356	0.269	0.560	0.439

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Statistical power of 1-quarter lagged real GDP growth predictors in the full sample (1982-2019) and sub-samples (1982Q2-2000Q4 and 2001Q1-2020Q1). For each predictor, we regress quarterly GDP against the lagged predictor and all combinations of the following lagged variables: the treasury term spread, the Federal funds rate, Consumer Price Index growth, Moody's BAA-AAA bond yield spread, and real GDP growth. The absolute t-statistic of the candidate predictor is reported for specifications yielding the largest/smallest predictor t-stat magnitude and adjusted R-squared.

Predictor	Period	Largest t-stat (magnitude)	Smallest t-stat (magnitude)	Highest AdjR2
	full sample	4.666	1.722	0.276
lnhys	1st half	4.778	3.059	0.263
	2nd half	2.310	0.577	0.183
	full sample	6.074	4.505	0.345
f_{sl}	1st half	2.334	1.493	0.200
	2nd half	7.146	4.166	0.397
	full sample	6.823	2.606	0.277
gz	1st half	2.582	1.248	0.183
	2nd half	5.122	1.501	0.242
	full sample	6.414	2.715	0.288
ebp	1st half	3.161	1.477	0.183
	2nd half	5.749	2.935	0.292
	full sample	7.246	2.769	0.332
nfci	1st half	3.747	1.536	0.240
	2nd half	6.211	3.701	0.331

Table 7: Sensitivity of 1-quarter lagged GDP predictors to individual quarters or years in the sample (1982-2019). The absolute t-statistic value for each of the candidate predictors is reported for various regression specifications after removing either a single quarter or a single calendar year from the sample. The reported statistic reflects the *lowest* absolute t-statistic that can be achieved by removal of one quarter or calendar year. The first three specifications refer to those from Table 6. For instance, the "Highest t-stat" specification for f_{sl} corresponds to the regression specification that results in the higher magnitude t-statistic in Table 6. The "Univariate" specification corresponds to a univariate regression of GDP growth against the corresponding lagged explanatory variable (in the column name). The "Bivariate" specification adds lagged GDP to the univariate specification.

	Specification	lnhys	f_{sl}	gz	ebp	nfci
Remove 1 qtr from...	Highest t-stat	3.951	4.419	5.885	5.176	5.935
	Highest AdjR2	2.259	3.141	2.851	3.262	3.518
	Univariate spec	2.774	4.061	5.564	4.503	3.657
	Bivariate spec	1.469	3.095	2.920	2.203	2.115
Remove 1 yr from...	Highest t-stat	2.995	3.200	4.555	3.984	4.526
	Highest AdjR2	1.507	2.386	1.811	2.483	3.167
	Univariate spec	1.982	2.522	4.187	3.248	2.357
	Bivariate spec	0.809	2.674	2.336	1.694	1.622

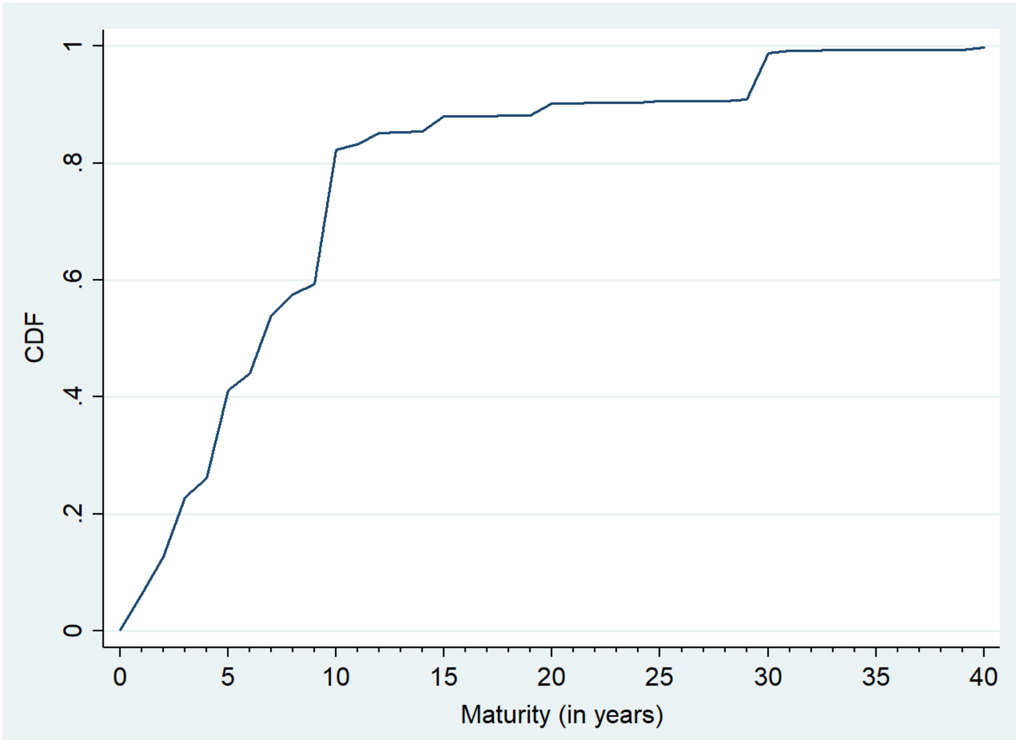
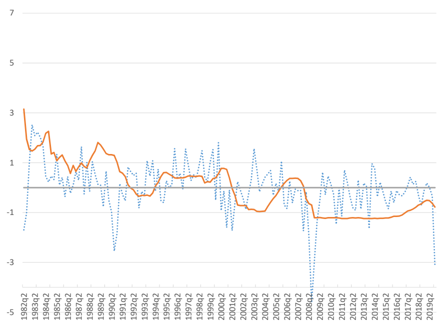
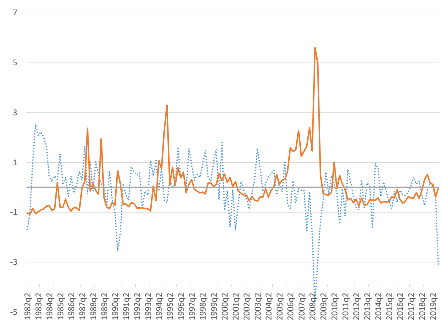


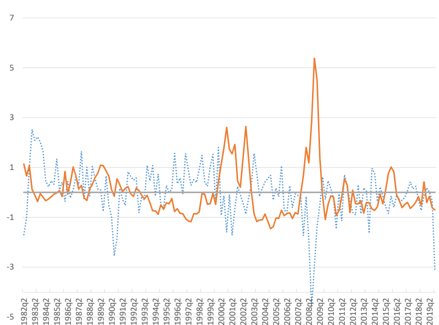
Figure 1:
Maturity distribution
The plot depicts the distribution of maturities in our sample of 43,526 rated bond issues in the Mergent FISD sample.



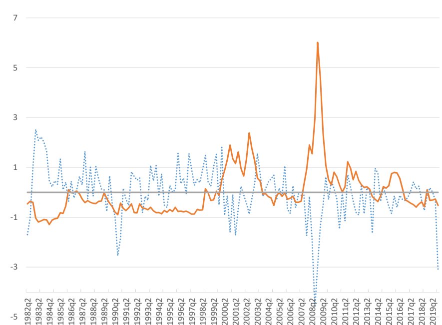
Federal funds rate



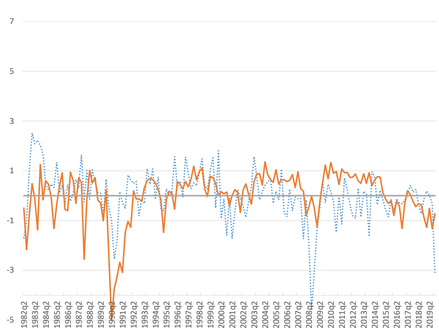
f_{sl}



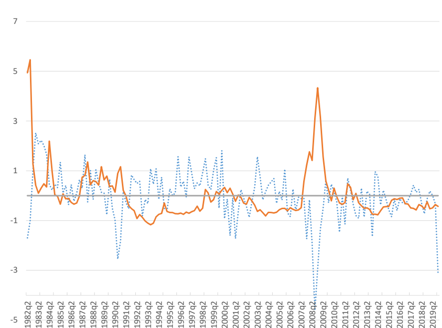
EBP



GZ



LnHYShare



NFCI

Figure 2:
Predicting Real GDP
The dashed line in each sub-figure depicts standardized real seasonally adjusted GDP growth, lagged by one quarter. Plotted against this are the various standardized macro variables (see the text for definitions).

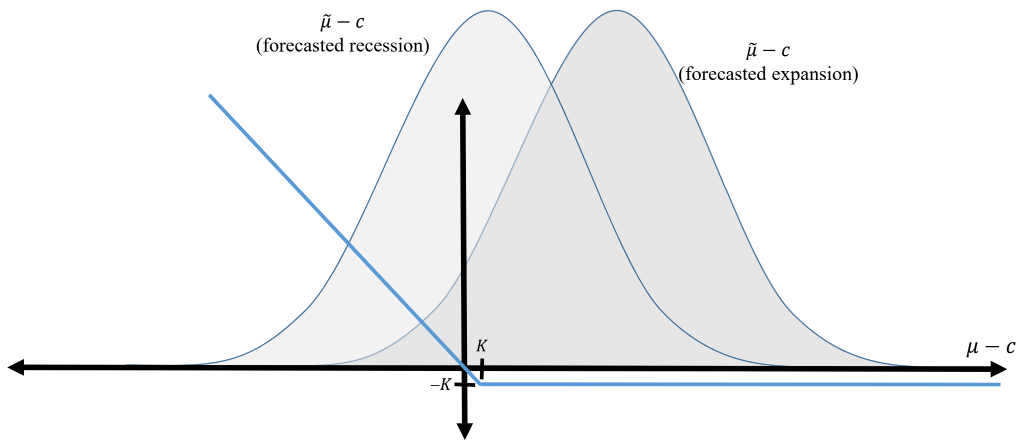


Figure 3:
Financing Trade-offs
The plot depicts the payoff diagram (thick blue line) trading off the benefits to the firm at date 0 of short term debt (i.e., avoiding expected operating losses at date 1) against the cost of refinancing operations at date 1. The quantity $\tilde{\mu} - c$ is the expected firm operating profits from the perspective of date 1 and K is the difference between refinancing costs and liquidation costs. Also depicted are two hypothetical expected profit distributions that could be realized at date 1. The distribution on the right (cf. left) reflects a forecast of economic expansion (cf. recession) at date 1.

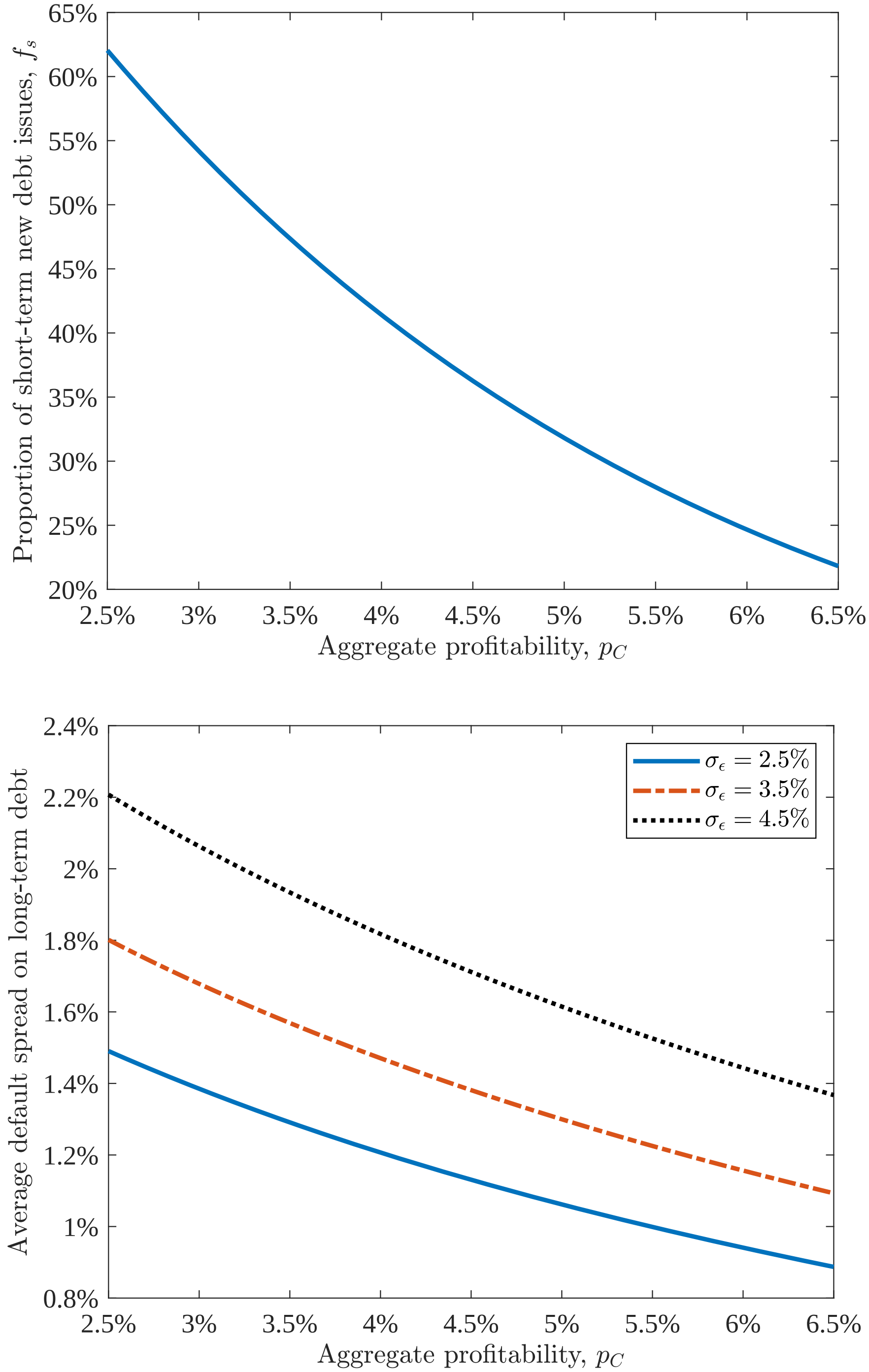


Figure 4:
Comparative statics of time-invariant model
Assuming model parameters are constant through time, the plots depict the steady-state share of short-term issuance (top) and average default spread on long-term bonds (bottom). The latter is shown under three distinct parameterizations of profit outcome volatility (on which the financing maturity choice does not depend).

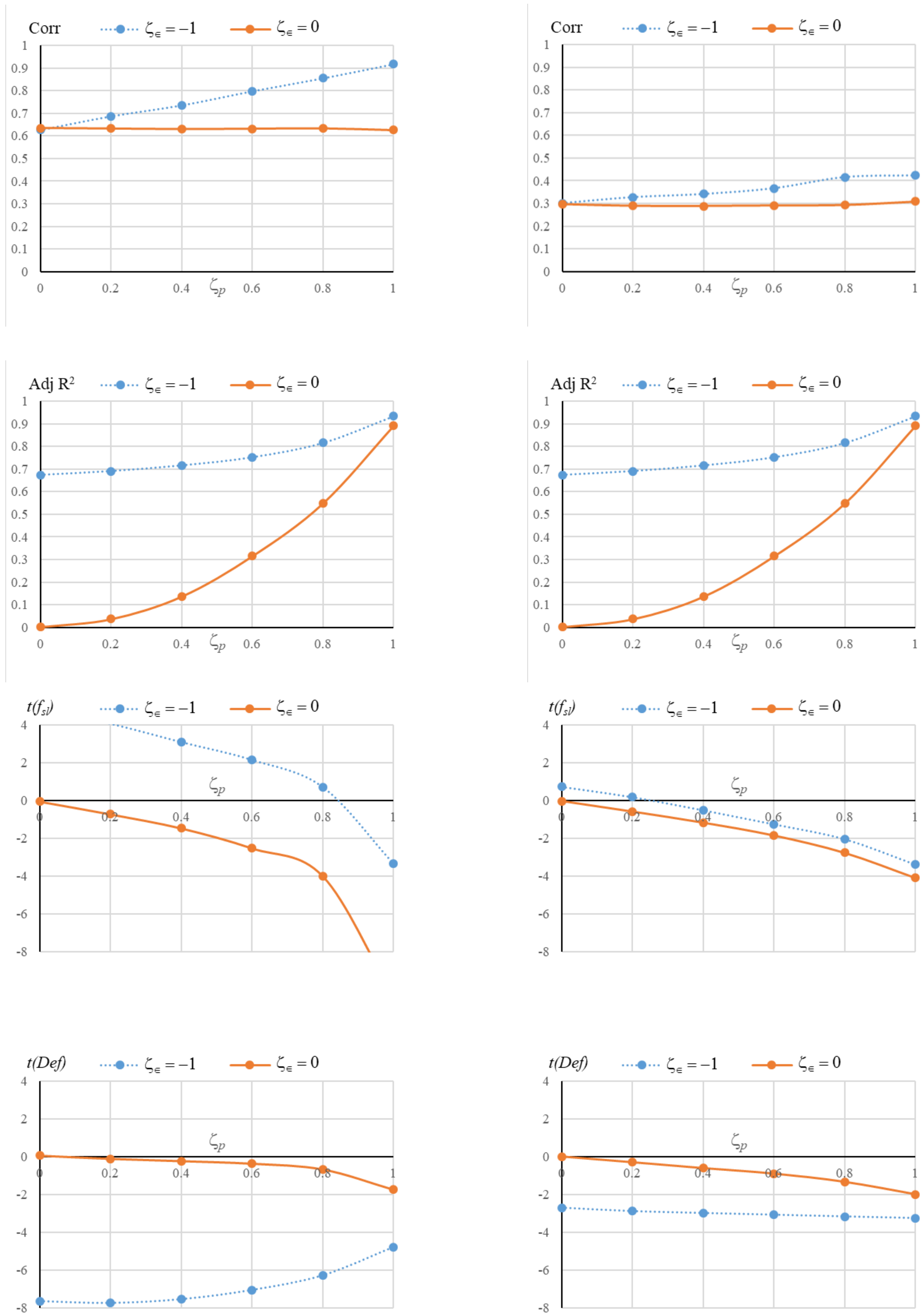


Figure 5:
Simulated dynamic model statistics
Time series model panels of 30 periods are simulated for GDP growth shocks, share of short-term issuance, $f_{s,t}$, and default premia, DEF_t. For each panel, correlations between $f_{s,t}$ and DEF_t are calculated, as well as statistics from regressing future GDP growth shocks on the two variables. The plots depict pooled statistics as a function of the presumed correlation between aggregate profitability and GDP (ζ_p) and profit outcome volatility and GDP (ζ_ϵ). Plots on the (left) right incorporate (no) variable observation errors.

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Appendix: Additional results

Tables A1 and A2 echo the analysis in Tables 3 and 4 using an annual, instead of quarterly, GDP growth forecasting horizon. Annual growth is defined to be

$$g^A_{t+4} = g_{t+1} + g_{t+2} + g_{t+3} + g_{t+4},$$

and the forecasting regression specification becomes

$$g^A_{t+4} = \beta_0 + \beta' \cdot y_t + \varepsilon_{t+4}.$$

Table A3 reports the results of running the last regressions from Tables 3, A1, 4, and A2 using Newey-West standard errors (with four lags).

The results indicate that f_{sl} remains a strong predictor of growth and that its forecasting power is relatively insensitive (within a statistical tolerance of one standard deviation) to the addition of alternative macro predictors that have appeared in the literature. In other words, the main observations about f_{sl} are unchanged: It is a highly significant predictor of growth containing information that is not subsumed by other well-established macro variables from the literature; moreover, f_{sl} appears to contain information about aggregate growth that is not found in v_{sl}. The main difference between the annual and quarterly regressions is that the predictive power of several of the other macro variables increases in prominence as the forecasting horizon increases from quarterly to annually.

Table A1: Repeating the regression analysis of Table 3 using annual growth. The regressions reported in this table echo ones Table 3 with the exception that the dependent variable is real and seasonally adjusted annual GDP growth. Specifically, each regression is of the form $g^A_{t+4} = \beta_0 + \beta' \cdot y_t$ where $g^A_{t+4} = g_{t+1} + g_{t+2} + g_{t+3} + g_{t+4} + \varepsilon_{t+4}$ (see Table 3 and the text for further details).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Term spread	0.506***	0.347*	0.513***	0.328*	0.538***	0.271	0.406**	0.469***	0.238	0.305*	0.384**	0.295*
	(0.146)	(0.136)	(0.145)	(0.138)	(0.144)	(0.145)	(0.139)	(0.138)	(0.132)	(0.127)	(0.130)	(0.132)
Fed funds rate	0.747***	0.730***	0.773***	0.716***	0.882***	0.226	0.796***	0.946***	0.490**	0.898***	0.992***	0.876***
	(0.163)	(0.148)	(0.162)	(0.149)	(0.169)	(0.187)	(0.154)	(0.160)	(0.176)	(0.145)	(0.155)	(0.246)
CPI growth	-0.476**	-0.547***	-0.504***	-0.541***	-0.431**	-0.483***	-0.496***	-0.346*	-0.479***	-0.517***	-0.409**	-0.443***
	(0.142)	(0.130)	(0.141)	(0.130)	(0.141)	(0.133)	(0.134)	(0.137)	(0.122)	(0.121)	(0.129)	(0.125)
BAA-AAA spread	-0.146	-0.121	-0.145	-0.119	-0.149	0.378*	0.234	0.521*	0.286	0.189	0.282	0.481*
	(0.158)	(0.144)	(0.156)	(0.144)	(0.155)	(0.184)	(0.171)	(0.213)	(0.171)	(0.153)	(0.202)	(0.207)
GDP growth	0.542***	0.389**	0.499**	0.394**	0.393*	0.339*	0.293	0.381*	0.0746	0.0532	0.164	0.0215
	(0.151)	(0.140)	(0.150)	(0.140)	(0.160)	(0.147)	(0.152)	(0.147)	(0.146)	(0.146)	(0.145)	(0.145)
f_{sl}		-0.671***		-0.737***					-0.514***	-0.628***	-0.559***	-0.516***
		(0.121)		(0.144)					(0.120)	(0.112)	(0.123)	(0.129)
v_{sl}			-0.263*	0.116								
			(0.125)	(0.137)								
LnHYShare					0.352*				0.446***	0.330**	0.357**	0.351**
					(0.141)				(0.123)	(0.121)	(0.124)	(0.130)
GZ						-0.942***			-0.750***			-0.191
						(0.197)			(0.194)			(0.349)
EBP							-0.743***			-0.615***		-0.429
							(0.167)			(0.150)		(0.269)
NFCI								-0.926***			-0.570**	-0.396
								(0.211)			(0.208)	(0.208)
Adjusted R^2	0.277	0.403	0.294	0.401	0.303	0.373	0.361	0.359	0.484	0.490	0.458	0.499

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Repeating the regression analysis of Table 4 using annual growth. The regressions reported in this table echo ones Table 4 with the exception that the dependent variable is real and seasonally adjusted annual GDP growth. Specifically, each regression is of the form $g^A_{t+4} = \beta_0 + \beta' \cdot y_t$ where $g^A_{t+4} = g_{t+1} + g_{t+2} + g_{t+3} + g_{t+4} + \varepsilon_{t+4}$ (see Table 4 and the text for further details).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
f_sl	-0.812***	-0.673***	-0.791***	-0.682***	-0.552***	-0.647***	-0.681***	-0.540***	-0.657***	-0.699***	-0.548***
	(0.130)	(0.129)	(0.151)	(0.129)	(0.131)	(0.129)	(0.132)	(0.128)	(0.129)	(0.132)	(0.130)
GDP growth		0.497***	0.500***	0.444**	0.230	0.367*	0.508***	0.0781	0.337*	0.465***	0.0724
		(0.129)	(0.129)	(0.134)	(0.150)	(0.147)	(0.136)	(0.159)	(0.149)	(0.138)	(0.157)
v_sl			0.217								
			(0.147)								
LnHYShare				0.182				0.323*	0.150	0.202	0.460**
				(0.130)				(0.129)	(0.131)	(0.134)	(0.145)
GZ					-0.505**			-0.617***			-0.872***
					(0.156)			(0.160)			(0.230)
EBP						-0.260			-0.234		0.196
						(0.146)			(0.147)		(0.226)
NFCI							0.0391			0.0879	0.234
							(0.136)			(0.139)	(0.154)
Adjusted R^2	0.206	0.275	0.281	0.280	0.319	0.286	0.270	0.343	0.287	0.277	0.358

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Regressions from Tables 3, A1, 4, and A2 using Newey-West standard errors (with four lags).

	(1) Table 3 (12)	(2) Table A1 (12)	(3) Table 4 (11)	(4) Table A2 (11)
Term spread	0.0682	0.295		
	(0.0447)	(0.162)		
Fed funds rate	0.348***	0.876**		
	(0.0893)	(0.300)		
CPI growth	-0.0917**	-0.443*		
	(0.0342)	(0.180)		
BAA-AAA spread	0.0568	0.481		
	(0.106)	(0.351)		
GDP growth	0.0461	0.0215	0.0836	0.0724
	(0.0644)	(0.157)	(0.0679)	(0.191)
f_{sl}	-0.188***	-0.516**	-0.161**	-0.548**
	(0.0493)	(0.186)	(0.0493)	(0.199)
LnHYShare	0.116*	0.351	0.155**	0.460*
	(0.0530)	(0.194)	(0.0477)	(0.207)
GZ	0.139	-0.191	-0.214**	-0.872*
	(0.121)	(0.438)	(0.0802)	(0.359)
EBP	-0.206*	-0.429	0.0582	0.196
	(0.0916)	(0.240)	(0.0835)	(0.270)
NFCI	-0.215*	-0.396	-0.0480	0.234
	(0.101)	(0.274)	(0.0667)	(0.174)
Adjusted R^2				

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$