Interest rate risk and corporate hedging*

Lorenzo Bretscher
LSE†

Philippe Mueller
LSE‡

Lukas Schmid
Duke§

Andrea Vedolin
LSE¶

Abstract

Uncertainty about the future path of interest rates severely adversely affects aggregate economic activity by depressing corporate investment. We provide significant empirical evidence to that effect and ask to what extent corporations can and do hedge interest rate risk using swaps. To that end, we compile a new, comprehensive hand collected data set on interest rate swap usage, and find that i) interest rate risk management significantly reduces expected default probabilities and credit spreads, and ii) helps firms attenuate the adverse effects of interest rate uncertainty on investment; iii) firms are on average floating rate payers, and iv) there are significant cross-sectional differences in swap usage according to asset and financing risk. To interpret these findings, we develop a dynamic model of corporate interest rate risk management in the presence of investment and financing frictions. Calibrating the model to our data, our setup quantitatively sheds new light on the aggregate effects of first versus second moments shocks to interest rates on economic activity.

Keywords: interest rate risk, risk management, frictions, corporate investment, credit risk

First Version: February 2015

This Version: July 2015

*We thank seminar participants at Hong Kong University of Science and Technology, Hong Kong University and the Arne Ryde Finance Workshop for their comments. Andrea Vedolin acknowledges financial support from the Economic and Social Research Council (Grant 1-RFM-C162).

†Department of Finance, Email: l.p.bretscher@lse.ac.uk

‡Department of Finance, Email: p.mueller@lse.ac.uk

§Fuqua School of Business, Email: lukas.schmid@duke.edu

¶Department of Finance, Email: a.vedolin@lse.ac.uk

As the slowing of the US Federal Reserve's quantitative easing program drives up interest rates, this imposes significant uncertainty on firms' financing conditions and future investment. A natural question is whether such uncertainty about the future path of interest rates affects the real economy. We start by documenting empirically that various measures of uncertainty about interest rates severely adversely affect aggregate economic activity, notably by depressing corporate investment. We then ask to what extent corporations can and do reduce their exposure to interest rate risk through hedging. One way of hedging interest rate risk is through the interest rate swap market. We document novel empirical evidence on the determinants of firms' interest rate risk management, and the relationship between swap usage and default risk. In particular, using a large panel of hand-collected data, we find that both financing and asset risk matters to explain the large cross-sectional differences in swap usage observed in the data. Notably, we find that swap usage helps mitigate the adverse effects of interest rate uncertainty on corporate investment, especially so for financially constrained firms. To interpret our empirical findings, we then develop a dynamic model of corporate investment, financing and hedging. Calibrated to our data, the model suggests that a positive shock to interest rate uncertainty depresses economic activity in similar magnitudes as a positive shock to the level of interest rates. This finding provides a novel perspective on the importance and effectiveness of central banks' forward guidance.

The starting point of our analysis is the observation that various measures of interest rate uncertainty are strongly negatively correlated with economic activity, and especially aggregate investment. Our preferred measure of interest rate uncertainty is Treasury Implied Volatility (TIV), a forward looking measure of interest rate uncertainty extracted from options, and first defined in Choi, Mueller, and Vedolin (2015). Going beyond raw correlations, we provide some more formal econometric evidence supporting an adverse effect of interest rate uncertainty on economic activity. In particular, we document that the effect holds at the aggregate level controlling for standard business cycle indicators such as credit spreads and more recently developed uncertainty measures such as the VIX and policy uncertainty indicators. Similarly, at the firm level, we document that interest rate uncertainty significantly depresses corporate investment holding investment opportunities constant. This begs the question: To what extent

can and do corporations mitigate these adverse effects through hedging their interest rate risk exposure?

The goal of this paper is to shed new light on the determinants of non-financial firms' interest rate risk management activity. We do so using a large cross-section of hand-collected data on publicly traded firms' interest rate risk hedging over the past twenty years. We begin by documenting that firms tend to be floating-rate payers on average. This finding is in contrast to earlier work which shows that firms tend to be fixed-rate payers. The reason for this discrepancy is twofold. First, firms in our data sample are larger than the ones used in previous studies. Larger firms own more long-term debt which pays fixed coupons and firms hedge this risk by entering a floating-for-fixed swap. Second, there is ample evidence that firms use interest rate swaps to time the market. When the term spread is steep, firms will want to lock in the low short-term interest rate, whereas in times of a flat or inverted term structure, companies prefer to pay a lower fixed rate on the long-term interest rate. The interest rate environment in the past ten years has been characterized by very low interest rates, especially at the short end of the curve which renders paying a floating rate more attractive.

We then document a significant and robust negative relationship between firm size and hedging activity. To this end, we define two main variables of interest: The percentage of outstanding debt that is swapped to a floating rate and total hedging, which is defined as the sum of the amount hedged (derivatives) and cash divided by book assets. The intuition behind the latter is that firms' risk management choice consists of either entering into (costly) derivatives positions or of holding cash. We find that small firms hedge more but not only through the cash channel but also through derivatives. For example, we find that the lower tercile of size sorted firms, swaps almost 10% of their outstanding debt whereas the upper tercile of firms swaps 7.5% of their outstanding debt. The difference is highly statistically different from zero. While univariate sorts are useful to build intuition, we then present novel evidence on the link between risk management, leverage and asset composition by means of double sorts. Interestingly, we find both asset and financing risk to matter. Small firms with low leverage and high Tobin's Q hedge the most. Intuitively, for low leverage firms default is not very likely, so that a high Tobin's Q signals growth opportunities going forward which is riskier than having assets in place.

Recent evidence documents a negative relationship between financial constraints and risk management. For example, using data on airline fuel hedging, Rampini, Sufi, and Viswanathan (2013) find that commodity price risk management is lower and even absent for firms that are more financially constrained. Moreover, risk management drops dramatically for severely financially distressed firms and recovers only slowly thereafter. These findings challenge the theoretical work of Froot, Scharfstein, and Stein (1993) who argue that firms engage in risk management because financing constraints make them effectively risk averse.

Our data allow us to empirically shed some light on the recently much debated links between financing constraints and hedging. Risk management may enhance value because it allows constrained firms to better take advantage of investment opportunities and avoid liquidity shortfalls. This suggests that more constrained firms should be expected to engage more in risk management. The recent empirical evidence in Rampini, Sufi, and Viswanathan (2013) challenges this view in case of the airline industry. Using a variety of proxies for financial constraints commonly used in the empirical literature, we find that constrained firms engage more in interest rate risk management, consistent with perceived intuition. On the other hand, distressed firms, as identified by high default probabilities and credit spreads, hedge their exposure only little. These results hold up both in univariate as well as in bivariate sorts. One potential eplanation for the conflicting recent evidence thus emerges in the context of interest rate risk management, namely the importance of carefully distinguishing between financial constraints and financial distress. While it is well known that common financial constraints indices have difficulties distinguishing between constraints and distress (see, e.g., Mensa and Ljungqvist (2014)), these types of firms are intuitively quite different. While financing constraints mostly pertain to firms with high growth opportunities whose growth is inhibited by limited access to external finance, distressed firms are those on the verge of bankruptcy, as discussed in Whited and Wu (2006). Our analysis shows that their hedging activity is also substantially different.

Finally, we also study the link between credit risk and hedging. In the presence of market imperfections, hedging reduces the probability of entering into costly financial distress (see, e.g., Smith and Stulz (1985)) and swap choice could be driven by the objective to minimize default costs (see, e.g., Jermann and Yue (2014)). To measure a firm's credit risk, we employ

data both on credit default spreads and an estimated probability of default. Using panel regressions, we find that the amount of hedging is a highly statistically significant determinant of both credit spreads and expected probabilities of default. For example, for any one standard deviation change in absolute percentage hedging, there is a 30 basis point (bp) decrease in the average five year credit spread and similarly, there is a 10 bp drop in the expected default probability. When we divide our sample into small and large firms, we find that small firms' default probabilities are more affected by hedging than those of large firms. These findings are robust and highly statistically significant controlling for other firm characteristics.

To explain the empirical findings, we develop a tractable model of a cross-section of firms which finance investment with defaultable short- and long-term debt and equity in the presence of aggregate interest rate risk, interest rate volatility risk and financial frictions. In the frictionless world of Modigliani and Miller (1958), hedging is irrelevant for the firm. With financial frictions, risk management can create value for firms as it allows them to absorb and react to shocks by transferring resources to states where they are most valuable. Two frictions provide a rationale for risk management in our model. Firms want to transfer funds to states so as to, first, avoid the deadweight costs associated with bankruptcy and, second, in order to avoid paying underwriting costs that come with equity issuance.

In our model, firms have access to two instruments for risk management purposes. First, they can enter into one-period interest rate swaps that allow them to exchange floating rate payments for fixed rate, or vice versa. Entering into a swap contract as a fixed rate payer entails transferring resources from future low interest rate to high interest rate states. This is because fixed rate payers obtain a positive payoff if the future short rate is above the swap rate they pay. Conversely, floating rate payers transfer resources from future high interest rate states to low interest rate states. Second, firms can accumulate cash which they can use to cover liquidity shortfalls. While swaps specifically hedge stochastic interest rates, cash holdings provide a cushion against any adverse shock but are disadvantaged through holding costs. In other words, swap contracts allow firms to transfer resources across future states, while cash reallocates current funds to future states symmetrically.

The model endogenously generates rich cross-sectional patterns about capital structure, default risk, and risk management, that are quantitatively in line with the empirical evidence.

Large firms have low market-to-book ratios, their high leverage mostly consists of long-term fixed rate debt, and they hold little cash. On the other hand, smaller firms tend to come with high market-to-book ratios, their lower leverage is mostly short-term, floating rate debt and they hold elevated amounts of cash.

Within the context of the model, there are two main channels, closely linked to financial frictions outlined above, that drive corporate swap choices. There is a *discount rate* channel, in which falling interest rates raise valuations and push larger firms to the equity issuance margin. Larger firms therefore want to transfer funds to future low interest rate states, and, thus, are net floating rate payers. Even unlevered firms are exposed to the discount rate channel, so that exposure directly affects the risk of firms' assets. On the other hand, there is a *financing* channel, in which rising interest rates push smaller firms relying on short-term floating rate debt closer to default. Small firms thus benefit from hedges against future high interest rates and are net fixed rate payers. Exposure to the financing channel depends on firms' financial structure, so that it directly affects financial risk. Hence, the model predicts and rationalizes cross-sectional differences in swap usage according to asset and financial risk. Further predictions are that the smallest firms self-select not to use swaps and that the aggregate net swap position thus depends on the endogenous size distribution. The model is thus qualitatively and quantitatively in line with the empirical evidence.

The model provides us with a useful laboratory to further quantitatively examine the determinants of swap usage through counterfactuals. While interest rate risk exposure is difficult to measure in the data as part of that exposure is already hedged, we can use the model to estimate exposure in a scenario in which swap contracts are unavailable. Comparing that scenario with the benchmark model with swaps we can back out the fraction of exposure that is optimally hedged as a function of firm characteristics and inform us about the value of swap availability and hedging. This also generates new insights into the cross-sectional determinants of interest rate risk exposure and swap usage as linked to financial and asset risk.

The rest of the paper is organized as follows. In the next section, we describe the data and present our main empirical findings. Section 2 presents a model of dynamic risk management together with a calibration. Finally, we conclude in Section 3.

Literature review: Our paper is related to the early literature on corporate risk management by Stulz (1984), Smith and Stulz (1985), Froot, Scharfstein, and Stein (1993), and Leland (1998). In their static setup, financing frictions are exogenously given and they show how corporate cash and risk management can create value by relaxing financial constraints.

More recently, a literature on risk management in dynamic models has emerged. Rampini and Viswanathan (2010) build a dynamic model of contracting frictions and show that hedging may not be optimal for firms with limited capital that they can pledge as collateral. In this setup, hedging demand competes for limited collateral with investment demand. They show that for growth firms the return on investment may be so high that it crowds out hedging demand.

In the model of Bolton, Chen, and Wang (2011), risk management operates through two channels: i) cash and ii) derivatives. Systematic shocks are mitigated by the latter, while idiosyncratic risk is managed through cash reserves.

While our paper shares the objective of that literature to deepen our understanding of firms' risk management practices, we focus more specifically on interest rate risk. This dictates and allows to fine tune our model to the specifics of interest rate risk exposure, while the previous literature has focused on more general representations of risk management. As a consequence, we introduce a dynamic model of a firm which explicitly considers short- and long-term debt, and cash, and thereby adds significant realism to the literature on dynamic firm models. Different from the papers referred to above, and importantly, our work also provides extensive empirical evidence on the determinants of interest rate risk management.

In related and complementary work, Vuillemey (2014) develops a model of bank interest rate risk management. In contrast to that, our empirical and quantitative work examines swap usage of non-financials.

In its focus on interest rate risk management using swaps, the paper perhaps closest to ours is Jermann and Yue (2014). They construct a dynamic general equilibrium model in which firms engage in interest rate risk management to avoid costly default. In their model, countercyclical idiosyncratic firm volatility makes firms fixed-rate payers on average. While we do not close

our model in general equilibrium, our model features rich cross-sectional heterogeneity that allows us to address the patterns uncovered in our empirical work.

1 Empirical Analysis

In this section, we first outline our data and then present our baseline empirical results. We start by documenting strong empirical links between measures of interest rate uncertainty and economic activity, both at the aggregate and at the firm level. We then proceed to empirically and quantitatively examine the cross-sectional and time series determinants of interest rate risk management.

1.1 Data

Our primary measure of interest rate uncertainty is Treasury Implied Volatility (TIV henceforth), as constructed in Choi, Mueller, and Vedolin (2015). Our results for other measures are similar. The Treasury Implied Volatility or TIV measure is defined in the spirit of the well known VIX index that is calculated by CBOE for the S&P 500 index. Our proposed TIV measure is the 30 year Treasury bond futures implied volatility, i.e. the square root of the implied variance.

We start with the sample consisting of all historical non-financial constituents of the S&P 500 index between 1994 and 2014.[1] We then augment this data set with hand-collected data on interest rate swap usage from EDGAR. Following Chernenko and Faulkender (2011), we use 10-K reports from the EDGAR database to determine the amount of floating-rate long-term debt and the notional amounts and directions of interest rate swaps outstanding at the end of each fiscal year. This allows us to calculate the net floating swap amount as the pay-floating-receive-fixed notional amount minus the pay-fixed-receive-floating notional amount. The result is then divided by the total debt outstanding at the end of the fiscal year to get the net share of the firm's debt that is swapped to floating. This variable can take values between -1 (all debt is swapped to fixed) and 1 (all debt is swapped to floating). In what follows, this variable is referred to as *% swapped*. The absolute value of this variable (|*% swapped*|) measures the

[1] We identify the historical S&P 500 constituents using CRSP.

net notional amount of interest swaps outstanding as a percentage of the firm's total debt and measures to which extent a firm engages in interest rate swaps. We also calculate the percentage of total debt that is floating both before (*initial % floating*) and after (*% floating*) consideration of the interest rate swap effects. These two variables take values between 0 and 1. We drop observations that do not provide enough information in their 10-K filings to determine the amount of floating rate debt or the notional amounts of outstanding interest rate swaps. This leaves us with 10,429 firm-year observations.

To study determinants of firms' hedging we also download firm specific information from Compustat. We calculate market *leverage* as total debt (long-term debt, DLTT, plus debt in current liabilities, DLC) divided by the market value of the firm which is calculated as book assets (AT) minus book equity (CEQ) plus the product of the share price at the end of the fiscal year (PRCC_F) and the number of shares outstanding (CSHO). Following Chernenko and Faulkender (2011) we calculate the percentage of debt that has more than five years to maturity as the difference between the overall amount of long-term debt (DLTT) and debt maturing in years two through five (DD2 - DD5), divided by total debt. This variable is referred to as *long-term debt*. The explanatory variable *cash* is cash (CH) scaled by book assets. A firm's *profitability* is measured as the ratio of operating income before depreciation (OIBDP) to book assets. Motivated by Froot, Scharfstein, and Stein (1993), we also include the sum of capital expenditures (CAPX) and acquisitions (AQC) scaled by book assets as a measure of *investment* in our analysis. Finally, we introduce *total hedging* as an alternative hedging variable. Risk management can take place both through derivatives usage and cash. The latter enables firms to forestall distress and default. Motivated by Bolton, Chen, and Wang (2011), we calculate this variable as the sum of cash and the absolute value of the net notional amount of interest swaps outstanding scaled by book assets. Following Whited and Wu (2006), we construct a financial constraints index where the authors define a firm to be financially constraint if it would like to raise an additional dollar of external capital but cannot do so because it faces a vertical supply of external capital curve. It is important to distinguish a firm from being financially constraint and distressed. We see the latter as a firm on the verge of bankruptcy and the former a young firm that would like to grow quickly but whose pace is restrained due to lack of financing.

To measure financial distress, we use two different variables: i) credit default swap (CDS) data and ii) probabilities of default. We obtain daily CDS data for the period from 2002 to 2012 from Markit. In our analysis, we merge the monthly average of the 5-year credit spreads in the respective fiscal-year-end month for each company in every year. We focus on the 5-year credit spreads as they are most liquid for the sample period. In addition, we also use firm-level expected probability of default (EPD) data which comes from the Risk Management Institute at National University of Singapore. A firm's probability of default is the purest measure of default risk as CDS prices or ratings can be driven by factors other than credit risk. We have monthly EPDs for the period from 1994 to 2013. To allow for a comparison of the results, we also focus on the 5-year EPD in the respective fiscal-year-end month for each company in every year.

1.1.1 Interest rate risk management summary statistics

In our data sample, 73.5% of all firms use swaps. Panel A of Table 1 reports summary statistics of interest rate swap usage and floating rate debt for our sample. For the average firm-year in our sample, 32.4% of the outstanding debt has a floating interest rate exposure. The average swap is equivalent to 6.5% of the firm's debt, but since some firms swap to floating while others swap to fixed, a net average of 1.1% of the firm-year's debt is swapped to a floating interest rate exposure, leaving the average firm-year with 33.7% of floating-rate debt.

[Insert Table 1 here.]

Note that different from earlier literature, we find firms to be floating-rate payers on average. For example, using a shorter data sample, Li and Mao (2003) and Chernenko and Faulkender (2011) document that firms tend to be fixed rate payers. To gauge in more detail this discrepancy, we divide our sample into small and large firms, where small (large) firms are those below (above) the median firm size. Firm size is a natural variable to study as much of the previous empirical literature on risk management has focussed on it. Following the theoretical insights of Froot, Scharfstein, and Stein (1993) more constraint firms should engage more in risk management activity. Hence, smaller firms should make more use of derivatives.

Stulz (1996) finds, however, that large companies make far greater use of derivative than small firms, even though small firms have more volatile cash flows and more restricted access to capital.

In Panel B and C, we report swap usage summary statistics for small and large firms, respectively. We first note that for the average firm-year in our sample, small firms have a much larger fraction of outstanding debt which has a floating rate exposure. For example, small firms have 37.9% of their initial debt with floating-rate exposure, while large firms only have 28.1%. Hence, the net average which is swapped to a fixed interest rate exposure is 0.6% for small firms, but large firms swap to a floating rate exposure which is 2.5% of the firm's debt. Abstracting from the direction of the swap, we find that in absolute terms, swap usage is similar between small and large firms: Small firms swap on average 6.6% of their outstanding debt, whereas large firms swap 6.5% thereof.

In Figure 1 and 2 we plot the absolute value of percentage swapped to floating and our total hedging variable for small and large firms over the years 1994 to 2013. Two observations are noteworthy. First, small firms consistently hedge more than large firms. Especially between 1994 and 2004, the discrepancy between small and large firms' hedging activity is very significant. Second, hedging has consistently increased from 1994 to 2004 and since then has been on a downward trend with the exception of the financial crisis when hedging both of small and large firms increased by more than 25%. Total hedging shows a clear time trend which is not surprising, given the tremendous increase in cash holdings over the past decade. The difference between small and large firms' total hedging is large and remains remarkably constant over the time span.

[Insert Figures 1 and 2 here.]

To gauge in more detail the difference between swap and non users, Table 2 reports firm characteristic for swap and non-swap users. Swap users tend to be larger firms, have a higher leverage ratio, a lower Tobin's Q, less cash, higher investments, are more profitable and have a lower cash flow volatility. Differences in firm characteristics are highly statistically different between swap users and non users.

[Insert Tables 2 and 3 here.]

Table 3 reports summary statistics on firm-specific variables expected to explain the cross-sectional difference in swap usage. We again divide our sample into small (Panel B) and large (Panel C) firms. In line with earlier literature, we find that small firms have a higher market-to-book ratio, a higher Tobin's Q, more cash, less leverage, and a higher cash flow volatility.

1.2 Interest rate uncertainty and economic activity

We now document empirical links between interest rate uncertainty as proxied by TIV and economic activity. We start by an analysis of aggregate relationships and then further break these down to the firm level.

1.2.1 Aggregate results

The starting point of our analysis is the pattern emerging from Figure 3, namely a striking negative comovement between TIV and aggregate investment. As a matter of fact, movements in TIV appear to lead movements in aggregate investment by some time: TIV rises, and with some delay, investment tends to fall.

[Insert Figure 3 here.]

While the figure shows nothing more than a simple correlation, we now document some more formal links between TIV and aggregate investment by means of predictive regressions. Table 4 reports the results. We use TIV along with a number of relevant forecasting variables to predict aggregate investment one year going forward.

[Insert Table 4 here.]

Perhaps not surprisingly, TIV enters negatively and significantly in a predictive regression along with the term spread and the short-term interest rate. More interestingly, it remains significant after controlling for various measures of credit spreads, which are well know indicators

of financial strain in the system and therefore aggregate economic conditions. In particular, they are typically taken as some of the strongest predictors of aggregate investment, as investment is often debt financed. Equally interesting is the observation that TIV remains negative and significant after inclusion of other variables likely proxying for uncertainty, such as the VIX and the overall economic policy uncertainty index introduced in Baker, Bloom, and Davis (2015). Although the predictive power of that index is especially strong, TIV remains strongly significant, which suggests that interest rate uncertainty in particular comes with adverse effects for the aggregate economy well beyond a broad index of economic policy uncertainty. This appears to be an observation relevant for the conduct of monetary policy.

To the extent that interest rate uncertainty adversely affects aggregate investment, we would expect that it also has effects on aggregate output. Table 5 confirms this intuition by reporting results from similar regressions predicting GDP one year ahead.

[Insert Table 5 here.]

Qualitatively, the results are similar. Notably again, TIV remains a significant predictor of GDP one year ahead controlling for financial conditions (credit spreads) and uncertainty indices. Importantly, interest rate uncertainty retains a special role above and beyond the general economic policy indicator.

These results suggest that interest rate uncertainty has significant adverse effects on the real economy, controlling for the standard predictive variables. While so far we are agnostic about the mechanism underlying these observations, an immediate and natural question is to what extent interest rate risk exposure moves with the TIX. All else equal, one would expect that corporations would attempt to reduce exposure in times of high interest rate risk. Figures 4 and 5 provide some preliminary evidence to that effect.

[Insert Figure 4 here.]

Figure 4 gives a representation of the overall fixed versus floating rate debt structure of the companies in our sample. The result is as striking as intuitive. Intuitively, one would expect that firms with a debt structure bent towards floating rate debt are more exposed to

interest rate risk and would like to reduce that in times of high interest rate uncertainty. This is precisely what the figure illustrates, and it does so in two ways. First, the amount of initial debt floating (before swap usage) tends to comove negatively with TIV, but also that firms increasingly make use of swaps such that the net debt position comoves even more negatively with TIV after swap usage.

The previous pattern suggests that firms usage of swaps also moves with TIV. Figure 5 illustrates that notion.

[Insert Figure 5 here.]

The Figure shows that in times of elevated interest rate uncertainty, firms' usage of cash flow swaps rises in proportion. In other words, when TIV is high, firms increasingly attempt to swap floating rate payments for fixed rate payments. The opposite pattern obtains in the case of fair value swaps.

1.2.2 Firm-level results

While we find the empirical linkages between TIV and aggregate economic activity instructive, they ultimately need to originate in firms' optimal response to interest rate uncertainty. Using panel regressions, we now document a number of stylized facts regarding the links between TIV and corporate policies at the firm level.

Table 6 reports predictive panel regressions on firm-level variables such as next year's investment, cash, hedging, |% swapped|, profitability, and % floating, using standard firm-level controls. Importantly, these controls include Tobin's Q, which is commonly interpreted as a measure of firms' investment opportunities. Including such a measure is crucial, in order to alleviate concerns that declines in investment are driven by declines in investment opportunities.

[Insert Table 6 here.]

Clearly, all dependent variables are significantly affected by interest rate uncertainty. In particular, an increase in interest rate uncertainty will lead to a decrease in investment, profitability, and % floating and an increase in cash, hedging, and |% swapped|. This is consistent with firms that become more cautious when interest rate uncertainty spikes. They cut investment projects in spite of profitable investment opportunities and decide to hedge more both using both cash and swaps. Moreover, they broadly appear to reduce their exposure to variable interest rates.

This is an important result as it confirms that the negative effect of interest rate uncertainty is not driven by a decline in investment opportunities. Rather, the highly significant negative coefficients on leverage and size in investment seem to give an important role to financing constraints and financing in the transmission from interest rate uncertainty to corporate policies. Table 7 explores this link further. We report regressions of predictive regressions of investment on firm-level controls when we condition on a variety of commonly used indices of financial constraints.

[Insert Table 7 here.]

The regression specifications change only marginally from column to column. In particular, we run very similar regressions for different proxies (or indices) for financial constraints. To measure to what extent a firm is financially constrained we use the Whited and Wu (2006), Altman (1968) Z-score, Hadlock and Pierce (2010) index, Kaplan and Zingales (1997) index, and size (in this order). The regressions include both the proxy of financial constraints as well as an interaction term of interest rate uncertainty with this proxy. From the interaction terms, we see that in most cases (WW index, Z-Score, and KZ index) financially constrained firms cut future investment more heavily compared to unconstrained firms.

1.3 Determinants of interest rate risk management

To understand in more detail the cross-sectional determinants of swap usage, we sort swap usage into terciles based on several firm characteristics (size, long-term debt, cash, and Tobin's Q). Panel A sorts % amount swapped, Panel B sorts the absolute % swapped, and Panel C

sorts total hedging. The results are reported in Table 8. In line with the results in Table 3, we note from Panel A, first column, that small firms are fixed-rate payers and swap on average 3.6% of their outstanding debt. Large firms are floating-rate payers and swap on average 3.4% of their initial exposure. The sorts also reveal that firms with more long-term debt and more cash tend to swap more (both in percentage and in absolute terms) and similarly, firms with a higher Tobin's Q are more prone to engage in swap usage.

[Insert Table 8 here.]

In absolute terms, we find that firms in the upper tercile of cash, swap 9.39% whereas firms in the lower tercile swap 7.12%. The difference is 2.27% and highly statistically different from zero. Similarly, firms in the lower tercile of Tobin's Q distribution, swap 6.56% whereas firms in the upper tercile swap 9.83%. The difference (3.27%) is again highly statistically different from zero. The same picture emerges from the total hedging variable which includes cash holdings. Small firms hedge 11.80% while large firms hedge 7.9%, the difference is 3.9% which is highly statistically different from zero. Similarly to the other variables, we also observe a strong negative relationship between Tobin's Q and the amount hedged.

We now provide evidence on the link between risk management, leverage and asset composition by means of double sorts. Tables 9 and 10 report results of sorting % swapped and absolute % swapped respectively along leverage and Tobin's Q (Panel A) and leverage and size (Panel B). The Tobin's Q sort clearly indicate a monotonic relationship between Tobin's Q and the amount hedged. A similar monotonicity arises for the leverage dimension: Firms with high Tobin's Q and low leverage hedge the most both in percentage and in absolute terms. Double sorting on size and leverage reveals that in absolute terms, small firms with low leverage hedge the most. Using total hedging in Table 11, we confirm the previous results: Small firms with low leverage hedge the most.

[Insert Tables 9, 10 and 11 here.]

Our results shed new light on the relationship of firm size and risk management activity. We find a strong negative relationship which is highly statistically significant accounting for

other firm characteristics. Moreover, we find that both asset and financing risk are important determinants of swap usage. Small firms are characterized by more cash, higher Tobin's Q and lower leverage. For lower leverage firms, default is not very likely whereas higher Tobin's Q implies higher asset risk. In line with this intuition, we find that low leverage firms with high Tobin's Q swap the most.

1.3.1 Risk management in constrained versus distressed firms

A recent debate in the literature concerns the links between firms' hedging policies and their financial constraints. In the presence of financial constraints risk management can enhance value as it allows firms to better align their investment and financing policies. On the other hand, in the frictionless world of Modigliani and Miller (1958), hedging is irrelevant for the firm. This therefore suggests that we should expect constrained firms to benefit more from hedging and thus engage more in risk management. Recent empirical evidence from airline fuel hedging as provided in Rampini, Sufi, and Viswanathan (2013) challenges this view by showing that risk management drops dramatically for firms approaching financial distress and recovers only slowly thereafter. We now reconsider this evidence in the context of corporate interest rate risk management.

To start our empirical investigation, we need proxies for financing constraints in the data. While measuring financing constraints at the firm level is difficult (see Mensa and Ljungqvist (2014) for a recent discussion), we rely on two common ones that we choose for their simplicity and widespread use. As a first pass, we use size as an indicator of financing constraints, capturing the notion that firms' growth is inhibited through financial constraints. A more refined version of that intuition is developed in Whited and Wu (2006), whose financial constraints index is among the most popular in the literature. A common concern with empirical financial constraints indices is that they do not clearly differentiate between financially constrained and financially distressed firms. While financial constraints prevent firms from exercising growth options, financially distressed firms are on the verge to default, a trait more widely associated with mature and older firms that have exhausted their growth potential. To account for these differences, we use two simple measures of financial distress, namely expected default probabilities and credit spreads. Beyond default probabilities, credit spreads contain a risk premium

compensating lenders for the systematic risk of default, as in Bhamra, Kuehn, and Strebulaev (2010) and Chen (2010).

[Insert Tables 12 and 13 here.]

Tables 12 and 13 report the main results by means of sorts. Panel A of Table 12 shows univariate sorts of our total interest rate risk hedging measure, namely the absolute percentage swapped, on the measures of financial constraints and distress discussed. The empirical patterns emerging are quite clear. Distressed firms hedge less and constrained firms hedge more, with the differences mostly being highly statistically significant. As we show next, these patterns also hold up in two-way sorts on both constraint and distress measures. Sorting two ways here is especially important, as our empirical proxies likely are correlated. Panels B and C of Table 12 show double sorts on constraints measures and CDS spreads, while Table 13 uses expected default probabilities as distress indicator. The results confirm the evidence from the univariate analysis. More financially constrained firms hedge more, even controlling for their distress risk, while more distressed firms hedge less, even controlling for their financing constraints. The results are generally statistically stronger when credit spreads are used as a distress indicator and size as a constraints measure, but they do also hold up with the other measures.

These findings suggest some perspective on the recent conflicting evidence between financial constraints and risk management, at least in the specific context of interest rate risk hedging. A well-known difficulty with measures of financial constraints is that they often identify financially distressed firms even though these are conceptually different. Our evidence thus corroborates the importance of carefully distinguishing between distress and constraints, and our two-way sorts are a step into that direction. Accordingly, interest rate risk hedging practices differ significantly between distressed and constrained firms, with the latter hedging more and the former less.

1.4 Interest rate risk management and corporate policies

1.4.1 Risk management and credit risk

One natural question is whether risk management helps reduce a firm's credit risk. In the presence of market imperfections, hedging reduces the probability of entering into costly financial distress (see e.g., Smith and Stulz (1985)). Figure 6 plots the average expected probability of default for small (upper panel) and large (lower panel) firms together with the absolute percentage of outstanding debt swapped for small and large firms, respectively. We note a strong negative relation between the two series. In the following, we examine more formally the link between hedging, credit spreads, and expected probabilities of default by means of cross-sectional regressions.

[Insert Figure 6 here.]

Table 14 reports pooled panel regressions from 5-year credit spreads onto initial percentage floating, percentage floating rate debt including swap effects, absolute amount swapped, and some firm variables known to be important determinants of spreads. We find that the initial percentage of floating debt is only marginally significant while the percentage floating rate debt including swap effects is not significant. This is not surprising as the direction of the hedge (i.e. whether a firm hedged from floating into fixed or from fixed into floating) should not matter. Moreover if hedging lowers credit risk, then after it has taken place, we do not expect the amount of floating rate debt to matter anymore. In contrast, we find the absolute value of percentage swapped to be significant and the coefficient carries the expected negative sign. The estimate is also economically significant, as we find that for any one standard deviation change in the absolute percentage swapped, credit spreads decrease by 30 bp. Other firm-specific variables such as leverage and cash flow volatility have the expected positive sign and are highly statistically significant.

[Insert Tables 14 and 15 here.]

Table 15 reports the same pooled panel regressions but now we use expected default probabilities as a left-hand side variable. Panel A depicts the regression results when we include

all firms. We note that the results are qualitatively the same as for the credit spreads and quantitatively even stronger: A larger amount swapped leads to a lower expected probability of default. The coefficient is highly statistically significant and has a negative sign. For any one standard deviation change in the absolute amount swapped, there is a 10 bp decrease in firms' default probability. Again, leverage and cash flow volatility are highly statistically significant and the adjusted R^2 is 23%. Panel B reports estimated coefficients when we divide our sample into small and large firms. We note that hedging is more significant for small firms than large firms, as the t-statistic decreases from -2.92 to -1.96. In terms of economic significance, we find that any one standard deviation change in hedging, reduces the probability of default of small firms by 14 bp and 10 bp for large firms.

2 Model

Motivated by the stylized evidence documented in the previous section, we now develop a dynamic model of corporate interest rate risk management. Apart from providing a quantitative rationale for our empirical findings, the model helps us i) disentangle the effects of asset and financing risk on interest rate risk management and ii) delineate interest rate risk exposure and management.

The model consists of two building blocks. First, a representation of the dynamics and the pricing of aggregate risks. Apart from stochastic interest rates and stochastic volatility in interest rates, we allow for aggregate productivity risks driving business cycle-like fluctuations. We directly parameterize a stochastic discount factor that specifies the pricing of interest rate and productivity risks. The second building block is a model of a cross-section of firms, which, given the stochastic discount factor and aggregate risks, choose optimal policies in the presence of financial frictions. Investment policies are chosen so as to maximize equity values and can be financed by retained earnings, equity issuance and, given a preferential tax treatment of debt, using leverage. Two types of debt contracts are available in our setup, namely short-term, floating rate debt, and long-term fixed rate debt. Firms can default on their outstanding debt if prospects are sufficiently bad, and we assume that there are deadweight bankruptcy costs associated with the ensuing restructuring process.

In the presence of financial frictions, engaging in risk management can be value enhancing for firms as it allows them to absorb and react to shocks by transferring resources to states where they are most valuable. Two frictions provide a rationale for risk management in our model. First, with costly default, firms have an incentive to transfer funds to low income states so as to avoid the deadweight costs associated with bankruptcy. Second, we model underwriting costs associated with equity issuance so that risk management can alleviate that burden, too.

In our model, firms have access to two instruments for risk management purposes. First and foremost, they can trade one-period interest rate swaps that allow them to exchange floating rate payments for fixed rate, or vice versa. Entering a swap contract as a fixed rate payer entails transferring resources from future low interest rate to high interest rate states. This is because fixed rate payers obtain a positive payoff if the future short rate is above the swap rate they pay. Conversely, floating rate payers transfer resources from future high interest rate states to low interest rate states. Second, firms can accumulate cash which they can use to cover liquidity shortfalls. While swaps specifically hedge stochastic interest rates, cash holdings provide a cushion against any adverse shocks but are disadvantaged through holding costs. In other words, swap contracts allow firms to transfer resources across future states, while cash reallocates current funds to future states symmetrically.

In the following, we provide a detailed description of the model, along with a calibration and a quantitative analysis.

2.1 Setup

We model a cross-section of firms in the presence of aggregate risks. The composition of the cross-section of firms changes over time, as firms exit upon default and new firms enter if prospects are sufficiently good. We determine entry endogenously below.

Aggregate Risk There are three sources of aggregate risk, namely stochastic changes in the

risk-free short-term interest rate, r_t, its volatility σ_{rt} and stochastic movements in aggregate productivity, x_t. The interest rate follows a Vasicek process with stochastic volatility, as

$$r_{t+1} = (1 - \rho_r)\bar{r} + \rho_r r_t + \sigma_{rt}\eta_{t+1}, \tag{1}$$

with $\eta_t \sim \mathcal{N}(0,1)$ and $0 < \rho_r < 1$. The long-run mean of the short rate is given by $\bar{r}$, the rate with which it reverts to this mean is given by ρ_r and its conditional volatility is given by σ_{rt}. The conditional variance σ_{rt}^2 follows the process

$$\sigma_{rt+1}^2 = (1 - \rho_\sigma)\bar{\sigma}_r^2 + \rho_\sigma \sigma_{rt}^2 + \sigma_w w_{t+1}. \tag{2}$$

Similarly, we set

$$x_{t+1} = (1 - \rho_x)\bar{x} + \rho_x x_t + \sigma_x \epsilon_{t+1} \tag{3}$$

as the stochastic process for aggregate productivity.

Following the literature on the cross-section of stock returns in production economies, we directly specify the stochastic discount factor that governs the pricing of aggregate risks. Given our emphasis on a detailed account of firm-level decisions, we view this as a parsimonious approach to capturing the dynamics of aggregate risk premia. The stochastic discount factor is given by

$$\log M_{t+1} = -r_t - \frac{1}{2}\lambda_r^2\sigma_{rt}^2 - \frac{1}{2}\lambda_\sigma^2\sigma_w^2 - \frac{1}{2}\gamma_t^2\sigma_x^2 - \lambda_r\sigma_{rt}\eta_{t+1} - \lambda_\sigma\sigma_w w_{t+1} - \gamma_t\sigma_x\epsilon_{t+1}, \tag{4}$$

where $\gamma_t = \gamma_0 + \gamma_1(x_t - \bar{x})$, and λ_r is the price of interest rate risk and λ_σ is the price of interest volatility risk. The process for the stochastic discount factor incorporates a number of relevant features. First, and importantly, there is discount rate risk through stochastic interest rates. In this respect, our specification is related to the one in Berk, Green, and Naik (1999). Second, in the model, aggregate productivity risk is priced and carries a time-varying price of risk γ_t. As a matter of fact, the process for γ_t implies a countercyclical price of risk, so that risk premia in the model are countercyclical as well. In capturing time-varying risk premia, we follow Zhang (2005). Accordingly, one interpretation of the process for γ_t is that it is a reduced-form representation of the time-varying risk aversion of a hypothetical investor. Countercyclical

risk premia are relevant in our context, in order to give a quantitatively realistic account of countercyclical borrowing costs faced by firms through credit spreads, which affects their risk management practices.

Firm Investment and Financing Apart from aggregate risks r_t and x_t, firms also face firm-specific profitability shocks, denoted $z_{i,t}$. We assume that i-th firm's profitability shock $z_{i,t}$ follows the mean-reverting process

$$z_{i,t+1} = \rho_z z_{i,t} + \sigma_z \xi_{i,t+1}. \tag{5}$$

The assumption that $z_{i,t}$ is firm-specific requires that $E[\xi_{i,t}\xi_{j,t}] = 0$, whenever $i \neq j$. Persistent firm-level shocks give rise to a non-degenerate cross-sectional distribution of firms at any point in time. This distribution changes over time for two reasons. First, firms adjust their policies in response to shocks, and second, firms default and new firms enter. We assume that before entry, potential entrants draw a realization of their profitability from the unconditional distribution of $z_{i,t}$. Given that signal, they make an entry decision, and upon entry, purchase a capital stock k_i. We assume that this capital stock is fixed for the life-time of the firm and think of it as a long-term project. Investment thus only takes place at entry, and we abstract from intermittent investment. We do this to retain tractability and keep the model solution computationally manageable. While modeling intermittent investment would add realism to our setup, none of the main qualitative implications would be affected. We describe the endogenous entry process in more detail below.

Once the capital stock is in place, firm i generates per-period, after tax profits $\pi_{i,t}$ given by

$$\pi_{i,t} = (1-\tau)(\exp(x_t + z_{i,t})k_i^\alpha - f), \tag{6}$$

where τ denotes the corporate tax rate, $0 < \alpha < 1$ is the capital share in production and f is a fixed cost incurred in the production process. Note that a capital share less than unity captures decreasing returns to scale.

In line with the US tax code, we assume that interest payments on corporate debt are tax deductible. For that reason, in the model, firms have an incentive to use leverage to finance expenditures. Accordingly, we assume that upon entry, firms can finance their initial capital stock using debt or equity. Issuing equity entails transaction costs. Initial debt comes in the form of a consol bond with a coupon d_i fixed at issuance. This specification captures the notion firms often try to align the maturity of their assets with the maturity of their liabilities, so that long-term projects come with long-term debt in our setup.

Because of fixed costs f and recurring coupon payments d_i, firms may potentially suffer liquidity shortfalls following a long sequence of adverse shocks, both aggregate and firm-specific. Firms can cover such episodes by issuing one-period, floating rate debt $b_{i,t}$ and by hording liquid assets in form of cash, $c_{i,t}$. While debt comes with a tax-advantage, it is defaultable and thus requires a time-varying premium $\delta_{i,t}$ over the risk-free rate, so that the net interest rate that firms pay is given by $r_t + \delta_{i,t}$. We determine the premium endogenously below. On the other hand, hording cash comes with a holding cost of ζ. Moreover, we assume that issuing short-term debt entails costs. More specifically, debt adjustment costs take the following form

$$\phi(b_{i,t}, b_{i,t+1}) = \phi_0 + \phi_1 |b_{i,t+1} - b_{i,t}|, \tag{7}$$

so that they contain a fixed and a proportional component. Note that as a consequence, firms can hold cash and short-term debt simultaneously, so that cash is not negative debt.

Risk Management and Swaps In the model, stochastic interest rates impose risks on firms through three channels. Clearly, there is *financing risk*, as movements in the short-term interest rate directly affect interest payments on corporate debt. Then, there is *discount rate risk* as short rates impact valuations through the pricing kernel. And third, there is *profitability risk* induced by the potential correlation between interest rates and aggregate productivity. In this context, firms may find it beneficial to partially hedge their exposure to interest rate risk. We account for this possibility by giving them access to one-period interest rate swaps.

More specifically, we assume financial intermediaries offer contracts that allow to exchange floating rate payments for a fixed swap rate one period ahead, or vice versa. We assume that

entering a swap contract entails a fixed cost ψ. This cost captures transactions costs associated with trading swaps in OTC markets, such as posting costly collateral. We denote the notional amount of swap contracts purchased at time t by s_t. Whenever $s_t > 0$, the firm is a net floating rate payer, while $s_t < 0$ indicates a net fixed rate payer. The swap rate equals the current short-term interest rate plus a swap spread sp_t. The swap spread is competitively priced, so as to equalize expected payments to both ends of the swap. In other words, we have

$$r_t + sp_t = E_t\left[M_{t+1} r_{t+1}\right]. \tag{8}$$

Two observations are in order. First, the swap spread can be negative. Second, we assume that promised swap payments have priority in bankruptcy, implying that even though firms' default is a possibility, they will always fully honor payments promised in the swap contract. Here we follow Bolton and Oehmke (2015), who detail the exclusion of swap contracts from automatic stay in bankruptcy. As a consequence, the swap pricing equation does not reflect default probabilities.

While swaps allow to transfer resources in a state-contingent manner, they entail fixed costs. On the other hand, cash allows to cheaply transfer across periods, but in a state-uncontingent fashion. In the model, a trade-off thus arises between conditional liquidity provision with swaps and unconditional liquidity with cash, similar as in Nikolov, Schmid, and Steri (2014).

We can now determine firms' net payout, denoted by $e_{i,t}$. Equity payout and financing decisions must satisfy the following budget constraint

$$\begin{aligned} e_{it} &= \pi_{i,t} - (1-\tau)d_i + b_{i,t} - \left(1 + (1-\tau)(r_{t-1} + \delta_{i,t-1})\right) b_{i,t-1} - \phi(b_{i,t-1}, b_{i,t}) \\ &\quad + \left(1 + (1-\tau)r_t - \zeta\right) c_{i,t-1} - c_{i,t} + s_{i,t-1}(r_{t-1} + sp_{t-1} - r_t) - \psi \mathbb{I}_{\{s_{i,t+1} \neq 0\}}. \end{aligned} \tag{9}$$

The budget constraint recognizes the tax deductibility of the coupon payments on long-term debt and on floating-rate short term date, as well as debt adjustment costs. Moreover, it explicitly states the holding costs ζ of cash. Finally, the last term captures payments arising from the swap position contracted last period, including the fixed cost associated with entering a new swap contract .

Note that e_{it} can take negative values. We interpret this capital inflow in the firm as a seasoned equity offering that entails issuance costs. Following the existing literature, we consider fixed and proportional costs, which we denote by λ_0 and λ_1, following Gomes (2001). Formally, we set

$$\lambda(e_{it}) = (\lambda_0 + \lambda_1 |e_{i,t}|)\mathbb{I}_{\{e_{i,t}<0\}}. \tag{10}$$

Distributions to shareholders, denoted by $d_{i,t}$, are then given as equity payout net of issuance costs,

$$d_{i,t} = e_{i,t} - \lambda(e_{i,t}). \tag{11}$$

Valuation The equity value of the firm, $V_{i,t}$, is defined as the discounted sum of all future equity distributions. We assume that equity holders will choose to close the firm and default on their debt repayments if the prospects for the firm are sufficiently bad, that is, whenever $V_{i,t}$ reaches zero. The complexity of the problem is reflected in the dimensionality of the state space necessary to construct the equity value of the firm. This includes both short-term interest rates, aggregate and firm-specific components of profitability, short- and long-term debt, cash holdings and swap positions. We can now characterize the problem facing equity holders, taking payments to bond holders as given. The value of these payments will be determined endogenously below. Shareholders jointly choose new short-term issuance, $b_{i,t}$, cash holdings $c_{i,t}$ and swap positions $s_{i,t}$ to maximize the equity value of each firm, which can then be computed as the solution to the dynamic program

$$V_{i,t} = \max\left\{0, \max_{b_{i,t},c_{i,t},s_{i,t}} \{d_{i,t} + E_t\left[M_{t+1}V_{i,t+1}\right]\}\right\}, \tag{12}$$

where the expectation on the left-hand side is taken by integrating over the joint conditional distributions of aggregate and idiosyncratic profitability shocks, and interest rates. Note that the first maximum captures the possibility of default at the beginning of the current period, in which case shareholders will get nothing. Note also, that implicit in this formulation is that the firm simultaneously defaults on short- and long-term debt.

We now turn to the determination of the required payments on short- and long-term debt, taking into account the possibility of default by equity holders. To do so, we need to make

assumptions about the recoveries accruing to both short-term and long-term debt holders in default. The total pool of creditors are assumed to recover the fraction of the firm's current assets and profits net of liquidation costs and any payments promised from swap contracts. The latter is consistent with our assumption that payments arising from the swap are senior in default. Formally, then, the default payoff is equal to

$$R_{i,t} = (1 - \xi)(\pi_{i,t} + k_i) + s_{i,t-1}(r_{t-1} + sp_{t-1} - r_t), \tag{13}$$

where ξ measures the proportional loss in default. Note that the requirement that recoveries are non-negative implicitly imposes limits on the amount of swap contracts the firm can enter. We then split the total recovery according to their respective market values into short-term debt recovery $R^s_{i,t}$ and long-term debt recovery $R^l_{i,t}$. Under these assumptions, the payments on short-term debt must satisfy the Euler condition

$$b_{i,t} = E_t \left[M_{t+1} \left((1 - \mathbb{I}_{\{V_{i,t+1}=0\}})(1 + r_t + \delta_{i,t}) b_{i,t}) + \mathbb{I}_{\{V_{i,t+1}=0)\}} R^s_{i,t+1} \right) \right]. \tag{14}$$

Similarly, the market value of long-term debt $B_{i,t}$ must satisfy the recursion

$$B_{i,t} = E_t \left[M_{t+1} \left((1 - \mathbb{I}_{\{V_{i,t+1}=0\}})(d_i + B_{i,t+1}) + \mathbb{I}_{\{V_{i,t+1}=0)\}} R^l_{i,t+1} \right) \right]. \tag{15}$$

Entry Depending on aggregate and firm-level conditions, a varying number of firms finds it optimal to close down, default on debt obligations and exit the economy. In order to allow for a long-run stationary economy, we complete the model with a specification of entry. We follow Gomes, Kogan, and Zhang (2003) and Gomes and Schmid (2012) in assuming that every period, there is a unit mass of potential entrant firms. These firms draw an entry cost $\chi_{i,t}$ in an iid fashion from a uniform distribution defined on the support $[0, X]$. At the same time, draw a signal about next period realization of their idiosyncratic profitability shock $z_{i,t+1}$. Conditional on that signal, firms enter whenever their maximum expected firm value exceeds the entry cost, that is, whenever

$$\chi_{i,t} \leq \max \left\{ 0, \max_{k_i, d_i} \left\{ E_t \left[M_{t+1}(V_{i,t+1} + B_{i,t+1}) \right] \right\} \right\}. \tag{16}$$

Firm-level investment $i_{i,t}$ is thus equal to $\chi_{i,t}$. The entry condition also pins down the average scale and long-term debt of newly entering firms. Note that the expected firm value upon entry depends on both aggregate conditions, that is current interest rates and aggregate productivity, as well as firm-level conditions, namely the signal about future firm productivity.

Discussion The previous paragraphs introduced a dynamic model of corporate interest rate risk management in the presence of financial frictions. The possibility of default and the associated deadweight costs of restructuring and liquidation give scope to value-enhancing hedging of aggregate interest rate risk by means of swaps. We now briefly discuss the basic mechanisms driving corporate policies and the dynamics of the aggregate cross-section of firms.

The entry condition (16) determines the evolution of the aggregate scale of the economy. Higher aggregate productivity and low interest rates forecast high valuations, low default and easier access to credit markets, with ensuing entry and investment waves. There are cross-sectional effects present in the model as well. Because potential entrants receive a signal about their future idiosyncratic profitability, more promising signals lead to elevated investment. On the other hand, decreasing returns to scale are reflected in cross-sectional differences in Tobin's Q among entrants. As a consequence, long expansions lead to the entry of larger firms on average, while the marginal firm entering in downturns is relatively smaller.

The scale of new entrants has important implications for the average debt structure in the cross-section. Larger firms find it easier to exploit the tax advantage of long-term debt, as they possess more collateral to support the corresponding coupon payments. At the same time, large firms' cash flows are more stable, as they are relatively less affected by fixed costs. As a result, they engage less in risk management and manage their liquidity needs more conservatively. Accordingly, they accumulate less cash and rely less on short-term debt.

Smaller firms, naturally, behave in the exact opposite way. They are smaller in scale, have higher Tobin's Q and exhibit more volatile cash flows. Consequently, risk management is more valuable to them and they thus need to rely more on cash and short-term debt to manage their liquidity needs.

What determines swap usage in the model? First of all, fixed costs make it relatively more costly for small firms to enter into a swap contract. All else equal, larger firms are thus more likely to use interest rate derivatives to hedge their exposure, and we expect non-swap users to be concentrated among smaller firms. Consequently, small firms will rely relatively more on cash as a risk management tool. Among swap users, however, smaller firms and firms with higher Tobin's Q make use of swap contracts more extensively. Given fixed costs of production and decreasing returns to scale, they are more exposed to interest rate risks and hedging that exposure is more valuable to them.

Which swap users will be fixed rate payers and which will be floating rate payers? Recall that floating rate payers transfer resources from future high interest rate states to low interest rate states. Intuitively, firms will thus tend to be net floating rate payers if their liquidity needs are concentrated in low interest rate states. Liquidity needs arise from two sources in the model. First, liquidity is valuable in states in which default is more likely because of deadweight costs associated with bankruptcy. Second, firms want to avoid paying costs associated with equity issuance. In the model, smaller firms have more short-term floating rate debt so adverse movements in interest rates push them closer to default as they have to refinance at a higher rate. They thus benefit from transferring resources to future high interest rate states, so that we expect them to be net fixed rate payers. This is the *financing* channel. On the other hand, falling interest rates increase valuations through the discount rate channel, which pushes large firms to the equity issuance margin, so that they benefit from transferring funds to low interest rate states. We refer to this as the *discount rate* channel. We expect them to be net floating rate payers. Similarly, by the preceding arguments, we intuitively expect the aggregate swap position in the economy to be related to the firm size distribution.

In the next section, we examine these predictions quantitatively by means of calibrations.

2.2 Calibration

The model is calibrated at an annual frequency. We summarize our parameter choices in Table 16. Our benchmark model requires that we specify 18 parameters belonging to three groups: seven for financing costs, seven for technology, and four for the specification of the stochastic discount factor which includes the stochastic process for the short rate. We pick a subset of

them to match moments pertinent to our analysis, namely about corporate credit spreads and default rates, leverage ratios, cash holdings and Tobin's Q, among others. We compute these empirical targets over the period from 1994 to 2014, consistent with our data sample on swap usage. Our choice of the remaining parameters follows the literature, but we do provide a sensitivity analysis with respect to them.

[Insert Table 16 here.]

The parameters determining the stochastic discount factor are the short rate process parameters ρ_r and σ_r, and the risk aversion parameters γ_0 and γ_1. For the purpose of our annual calibration, we identify the short rate with the one-year US Treasury rate, which exhibited an annual autocorrelation of 0.86 and an annual volatility of 2.23% with a mean of 3.17% between 1994 and 2014, and pick the parameters accordingly. Our calibration strategy for the risk aversion parameters is linked to empirical targets in the corporate bond market. In particular, we choose γ_0 and γ_1 to roughly match the average level and the volatility of the 10 year credit spread in our sample. The notion that risk aversion parameters can be linked to credit spreads has recently received some attention in the literature under the label 'credit spread puzzle', referring to the observation that average spreads are too high to be explained by average losses in default alone. Rather, as a number of papers have pointed out (see e.g. Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010), Bhamra, Kuehn, and Strebulaev (2010)), credit spreads are thought to contain a sizeable credit risk premium compensating investors for the fact that most losses in default occur in downturns, when marginal utility is highest. That premium and its volatility, in turn, depend on risk aversion. Since default costs represent one rationale for risk management in our model, matching credit spread dynamics appears relevant.

The next batch of parameters falls under the label technology, and comprises the aggregate and firm-level shock process parameters ρ_x, σ_x, ρ_z and σ_z, returns to scale α, fixed costs f and the corporate tax rate τ, although the latter might be more accurately labeled as an institutional parameter. We set the capital share α of production equal to 0.65 in line with the evidence in Cooper and Ejarque (2003). We calibrate f to 0.03, similar to Gomes (2001). This choice is consistent with observed levels of firm-level profitability. At the firm level, we

calibrate the volatility σ_z and persistence ρ_z of the idiosyncratic productivity process to match the cross-sectional dispersion in leverage and profitability. The effective corporate tax rate τ is 14%, consistent with the evidence in van Binsbergen, Graham, and Yang (2010). Finally, our parameterization of the aggregate productivity process follows Cooley and Prescott (1995), and is standard in the business cycle literature.

Lastly, we need to calibrate the parameters pertaining to firms' financing. That choice quantitatively determines the magnitude of financial frictions that firms face, and thus their incentives to engage in risk management. The relevant parameters are the issuance costs for debt and equity, that is, λ_0 and λ_1, and ϕ_0 and ϕ_1, respectively, the bankruptcy costs ξ, the cash holding cost ζ, and the swap issuance cost ψ. We start by setting the issuance cost parameters in both equity and debt markets to match the size and frequency of new issuances. These choices also help us matching realistic leverage ratios and cash holdings. In general, our parameter choices are consistent with the estimation results in Gomes (2001), Hennessy and Whited (2005), Hennessy and Whited (2007), and Altinkilic and Hansen (2000). When it comes to bankruptcy costs, Andrade and Kaplan (1998) report default costs of about 10% to 25% of asset value and Hennessy and Whited (2007) estimate default losses to be around 10%. Our choice is thus in line with the empirical evidence, by set bankruptcy costs ξ to 20%. This choice also allows us to get realistic levels of credit spreads. We choose the cash holding cost ζ to match average cash holdings in the model. Our choice is also consistent with the estimation evidence in DeAngelo, DeAngelo, and Whited (2011). Finally, there is very little guidance when it comes to calibrating the swap issuance cost ψ. We set it to match the relative number of swap users relative to non swap users.

Most of our quantitative results are based on simulations. Rather than repeating the simulation procedure, we summarize it here. We create artificial panels comparable to the sample in our empirical work. We thus simulate 800 firms over a period of 20 years. To avoid dependence on arbitrary initial conditions, we simulate 500 years, but drop the first 480 years when computing model statistics. We repeat that procedure 100 times.

2.3 Quantitative Results

We start by assessing the overall quantitative fit of the model by looking at basic firm-level moments, before we turn to the cross-sectional firm distribution and, more specifically, the implications for swap usage. Table 17 reports unconditional moments generated by the model and their empirical counterparts and shows that they are generally consistent with the data. We focus on firm-level moments related to financing and investment policies, and aggregate moments related to interest rates on government and corporate bonds.

[Insert Table 17 here.]

Related to firm-level policies, the table shows cross-simulation averages of the average market leverage and its cross-sectional dispersion, the frequency and size of new equity issuances, average market-to-book ratio, cash holdings and default rates, and finally average profitability and its cross-sectional dispersion. It illustrates that the corporate financing and investment policies are generally consistent with the data.

Since the goal of this paper is to generate realistic incentives for risk management induced by costly default, it is important that the model-implied leverage ratios are compatible with empirical estimates. In the model, average market leverage and its dispersion are close to empirical estimates. Given the substantial tax benefits to debt, generating realistically low leverage ratios is often challenging for structural models of credit risk, an observation referred to as the low-leverage puzzle. In our setup with priced aggregate risk as well as financial frictions, firms optimally choose low leverage in order to preserve borrowing capacity for bad times. Another motive for risk management in the model is avoidance of equity issuance costs. In that respect, the model generates infrequent, but rather sizable equity issuances in line with the data. While average Tobin's Q is slightly low relative to the empirical counterpart, this may partially due to the specifics of our sample period, which includes the significant run ups in valuations around the dotcom boom. In fact, our model estimate is much closer to long-run average. While we could simply match Tobin's Q in the model by lowering fixed costs f, this would make it harder to generate realistic profitability statistics, which are important for risk management purposes. Given significant aggregate and idiosyncratic risks, firms choose to

hold a sizeable amount of cash, in line with the data, in spite of considerable holding costs. While in the data cash holdings are used for a variety of reasons, in the model they represent a vehicle for precautionary savings and thus a risk management tool, potentially complementary to hedging by means of swaps. Finally, and importantly, the model is quantitatively consistent with the recent US default experience.

The model matches the dynamics of the short-rate - taken to be the one-year Treasury rate - well. This is by constructions, as this is a purely exogenous process that we can directly calibrate. Needless to say, an accurate representation of interest rate risks is important for our purposes. Equally important, and perhaps more challenging, is to replicate the empirically observed dynamics of credit spreads. As the table indicates, the model rationalizes these quite well. As alluded to earlier, the challenge in generating realistic credit spread levels and dynamics, lies in the observation that expected losses empirically are not sufficient to rationalize the observed levels of credit spreads. Rather, since default losses end tend to occur in bad times, bond holders additionally need to be compensated for this systematic risk exposure, so that credit spreads contain a potentially large credit risk premium. Our specification of the stochastic discount factor which accounts for priced systematic productivity risk allows us to match that aspect of the data. Importantly, the fact that $\gamma_1 < 0$ implies that the credit risk premium is countercyclical, which exacerbates the average premium and its volatility.

Given our emphasis on the cross-sectional determinants of swap usage, it is important that the model generates a realistic cross-section of firm characteristics. Table 18 reports the results by means of simple correlations between firm characteristics. While perhaps not surprisingly slightly high, the correlations are generally qualitatively in line with their empirical counterparts. A few of the correlations are noteworthy. To begin with, larger firms tend to have higher leverage ratios. In the model, this occurs because larger firms have more collateral to support coupon payments at entry. Firms have an interest in exploiting collateral for leverage as it allows them to shield more profits from taxes. Importantly, as debt financing at the entry stage comes in from of a consol bond, larger firms also tend to have a larger share of fixed rate debt in their bond portfolio. Recall that short-term debt comes in form of a one-period floating rate bond, so that the model rationalizes the data on the fixed vs floating mix qualitatively rather well. Decreasing returns to scale help the model reconcile the empirical links between

Tobin's Q and size, in that smaller firms have higher market-to-book ratios. Note that since a firm's scale is fixed at entry, future investment is not compounded into firm value. This is why in the model that correlation is weaker than in the data. Accounting for intermittent investment would bring the model closer to the empirical counterpart. As noted, we abstract from that relevant extension of the model purely for computational reasons. Finally, smaller firms hold more cash, both in the model and in the data. In the context of the model, smaller firms have a higher precautionary savings motive, as they have more volatile cash flows and are more likely to face various fixed costs.

[Insert Table 18 here.]

Fixed costs also help the model rationalize various stylized facts about swap usage in the data. First of all, a significant fraction of firms does not use swaps at all. Such firms tend to be smaller, have higher market-to-book, lower leverage and more cash. On the other hand, conditional on being a swap user, we showed empirically, that smaller firms use swaps more extensively. Within the context of the model, this is rationalized by the fixed cost of entering a swap contract, ψ, which is calibrated to match the fraction of swap users among firms. As Table 19 shows, the model rationalizes that fraction essentially by construction. Small firms find fixed costs relatively more costly, so that they are more hesitant to enter into a swap contract. On the other hand, once the fixed cost is expensed, they swap more, given their higher exposure. The model also matches the percentage and the absolute percentage of debt swapped rather well.

[Insert Tables 19 and 20 here.]

Turning to the cross-sectional implications of the model, Table 20 reports unconditional univariate sorts of absolute percentage of debt swapped and percentage swapped, respectively, along various firm characteristics. Qualitatively, the model replicates the empirical evidence well. As already described above, conditional on paying the fixed costs associated with entering into swap contracts, small firms hedge more, and when they do so, they tend to be fixed rate payers. The intuition is as follows. As alluded to previously, floating rate payers transfer

resources from future high interest rate states to low interest rate states. Intuitively, firms will thus tend to be net floating rate payers if their liquidity needs are concentrated in low interest rate states. In the model, smaller firms have more short-term floating rate debt so adverse movements in interest rates push them closer to default as they have to refinance at a higher rate. While smaller firms' liquidity needs are thus concentrated in high interest rate states, and they therefore tend to be fixed rate payers, larger firms liquidity needs are concentrated in low interest rate states, as rising valuations in the aftermath of falling short-rates push them to the equity issuance margin. Those firms, accordingly, tend to be floating rate payers. Similarly, firms with a higher proportion of long-term debt in their bond portfolio, use swaps less extensively and if they do, the tend to be floating rate payers. In the context of the model, this is because firms with a higher fraction of long-term debt tend to be larger, so that they tend to exhibit less volatile cash flows, and thus hedge less on average, and benefit from transferring resources to low interest rate states, so they end up being floating rate payers. Similarly, firms with high cash holdings and higher Tobin's Q tend to use swaps more extensively, and are fixed rate payers on average, as they tend to be smaller.

The following tables document unconditional double sorts of absolute percentage of debt swapped and percentage swapped, respectively, along various firm characteristics, similar to the empirical work. The Tobin's Q sort clearly indicate a monotonic relationship between Tobin's Q and the amount hedged. A similar monotonicity arises for the leverage dimension: Firms with high Tobin's Q and low leverage hedge the most both in percentage and in absolute terms. Double sorting on size and leverage reveals that in absolute terms, small firms with low leverage hedge the most, consistent with the empirical evidence.

3 Conclusion

This paper presents novel empirical evidence on risk management behavior of non-financial firms. Our findings can be summarized as follows: First, interest rat risk management significantly helps mitigate the adverse affects of interest rate risk uncertainty, second, there are significant cross-sectional differences in swap usage according to asset and financing risk, and third, interest rate risk management significantly reduces expected default probabilities and credit spreads. We then propose a tractable and parsimonious dynamic model which rationalizes and quantitatively matches the data.

There are several interesting avenues for future research. In our model, we impose an exogenous process for the risk-free short-term interest rate while in reality, interest rates are set by the Central Bank. With looming higher interest rates in the near future, it is natural to ask how monetary policy affects firms' optimal risk management. For example, higher interest rates affect both firms' financing and asset risk, and the associated cross-sectional distribution. We leave this exciting topic for the future.

References

Altinkilic, O., and R. Hansen (2000): "Are There Economies of Scale in Underwriting Fees? Evidence of Rising External Financing Costs," *Review of Financial Studies*, 13(1), 191–218.

Altman, E. (1968): "Discriminant Analysis and the Prediction of Corporate Bankruptcy," *Journal of Finance*, 23, 589–609.

Andrade, G., and S. Kaplan (1998): "How Costly Is Financial (Not Economic) Distress? Evidence from Highly Leveraged Transactions That Became Distressed," *Journal of Finance*, 53(5), 1443–93.

Baker, S. R., N. Bloom, and S. J. Davis (2015): "Measuring Economic Policy Uncertainty," Working Paper, Stanford University.

Berk, J., R. C. Green, and V. Naik (1999): "Optimal Investment, Growth Options, and Security Returns," *Journal of Finance*, 54, 1553–1607.

Bhamra, H. S., L.-A. Kuehn, and I. A. Strebulaev (2010): "The Levered Equity Risk Premium and Credit Spreads: A Unified Framework," *Review of Financial Studies*, 23(2), 645–703.

Bolton, P., H. Chen, and N. Wang (2011): "A Unified Theory of Tobin's Q, Corporate Investment, Financing and Risk Management," *Journal of Finance*, 66, 1545–1578.

Bolton, P., and M. Oehmke (2015): "Should Derivatives Be Privileged in Bankruptcy?," forthcoming. Journal of Finance.

Chen, H. (2010): "Macroeconomic Conditions and the Puzzles of Credit Spreads and Capital Structure," *Journal of Finance*, 65(6), 2171–2212.

Chen, L., P. Collin-Dufresne, and R. S. Goldstein (2009): "On the Relation Between Credit Spread Puzzles and the Equity Premium Puzzle," *Review of Financial Studies*, 22, 3367–3409.

Chernenko, S., and M. Faulkender (2011): "The Two Sides of Derivatives Usage: Hedging and Speculating with Interest Rate Swaps," *Journal of Financial and Quantitative Analysis*, 46, 1727–1754.

Choi, H., P. Mueller, and A. Vedolin (2015): "Bond Variance Risk Premiums," Working Paper, London School of Economics.

Cooley, T. F., and E. C. Prescott (1995): "Economic Growth and Business Cycles," *Frontiers of Business Cycle Research*, pp. 1–38.

Cooper, R., and J. Ejarque (2003): "Financial Frictions and Investment: A Requiem in Q," *Review of Economic Dynamics*, 6, 710–728.

DeAngelo, H., L. DeAngelo, and T. M. Whited (2011): "Capital Structure Dynamics and Transitory Debt," *Journal of Financial Economics*, 99, 235–261.

Froot, K. A., D. S. Scharfstein, and J. C. Stein (1993): "Risk Management: Coordinating Corporate Investment and Financing Policies," *Journal of Finance*, 48, 1629–1648.

Gilchrist, S., and E. Zakrajšek (2012): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102, 1692–1720.

Gomes, J. F. (2001): "Financing Investment," *American Economic Review*, 91, 1263–1285.

Gomes, J. F., L. Kogan, and L. Zhang (2003): "Equilibrium Cross-Section of Returns," *Journal of Political Economy*, 111, 693–732.

Gomes, J. F., and L. Schmid (2012): "Equilibrium Credit Spreads and the Macroeconomy," Working Paper, University of Pennsylvania.

Hadlock, C. J., and J. R. Pierce (2010): "New Evidence on Measuring Financial Constraints: Moving beyond the KZ Index," *Review of Financial Studies*, 23, 1909–1940.

Hennessy, C., and T. M. Whited (2005): "Debt Dynamics," *Journal of Finance*, 60, 1129–1165.

——— (2007): "How Costly Is External Financing? Evidence from a Structural Estimation," *Journal of Finance*, 62(4), 1705 – 1745.

Jermann, U. J., and V. Z. Yue (2014): "Interest Rate Swaps and Corporate Default," Working Paper, University of Pennsylvania.

Kaplan, S. N., and L. Zingales (1997): "Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints?," *Quarterly Journal of Economics*, 115, 707–712.

Leland, H. E. (1998): "Agency Cost, Risk Management, and Capital Structure," *Journal of Finance*, 53, 1213–1243.

Li, H., and C. X. Mao (2003): "Corporate Use of Interest Rate Swaps: Theory and Evidence," *Journal of Banking and Finance*, 27, 1511–1538.

Mensa, J. F., and A. Ljungqvist (2014): "Do Measures of Financial Constraints Measure Financial Constraints?," Working Paper, Harvard Business School.

Modigliani, F., and M. H. Miller (1958): "The Cost of Capital, Corporate Finance, and the Theory of Investment," *American Economic Review*, 48, 261–297.

Nikolov, B., L. Schmid, and R. Steri (2014): "Dynamic Corporate Liquidity," Working Paper, University of Lausanne.

Rampini, A. A., A. Sufi, and S. Viswanathan (2013): "Dynamic Risk Management," *Journal of Financial Economics*, 111, 271–296.

Rampini, A. A., and S. Viswanathan (2010): "Collateral, Risk Management, and the Distribution of Debt Capacity," *Journal of Finance*, 65, 2293–2322.

Smith, C. W., and R. Stulz (1985): "The Determinants of Firms' Hedging Policies," *Journal of Financial and Quantitative Analysis*, 20, 391–405.

Stulz, R. (1984): "Optimal Hedging Policies," *Journal of Financial and Quantitative Analysis*, 19, 127–140.

——— (1996): "Rethinking Risk Management," *Journal of Applied Corporate Finance*, 9, 8–24.

van Binsbergen, J. H., J. Graham, and J. Yang (2010): "The Cost of Debt," *Journal of Finance*, 65, 2089–2136.

Vuillemey, G. (2014): "Derivatives and Risk Management by Commercial Banks," Working Paper, Sciences Po Paris.

Whited, T., and G. Wu (2006): "Financial Constraints Risk," *Review of Financial Studies*, 19, 531–559.

Zhang, L. (2005): "The Value Premium," *Journal of Finance*, 60, 67–103.

4 Tables

Table 1
Swap usage and floating rate debt summary statistics

This table reports summary statistics for swap usage and floating-rate debt percentages for the sample of non-financial firms. The sample period is 1994 to 2013. Swap users are firms that use interest rate swaps at least once during the sample period. Initial % floating percentage of outstanding debt that is floating before accounting for the effect of interest rate swaps. % floating is the percentage of outstanding debt that is floating after accounting for the effect of interest rate swaps. % swapped is the percentage of outstanding debt that is swapped to a floating interest rate and |% swapped| is the absolute value of this. Long-term debt is the percentage of outstanding debt that has more than 5 years to maturity.

variable	N	mean	stdev	min	max
Panel A: All companies					
initial % floating	10,084	32.475	28.308	0	100
% swapped	10,429	1.080	15.717	-100	100
|% swapped|	10,429	6.511	14.346	0	100
% floating	10,084	33.709	27.423	0	100
long-term debt	9,384	45.318	28.340	0	100
Panel B: Small firms					
initial % floating	4,515	37.875	33.061	0	100
% swapped	4,778	-0.580	17.350	-100	100
|% swapped|	4,778	6.558	16.073	0	100
% floating	4,515	37.452	31.466	0	100
long-term debt	4,232	39.777	32.800	0	100
Panel C: Large firms					
initial % floating	5,569	28.096	22.852	0	100
% swapped	5,651	2.485	14.040	-100	100
|% swapped|	5,651	6.471	12.705	0	100
% floating	5,569	30.673	23.206	0	100
long-term debt	5,152	49.870	23.095	0	100

Table 2
Firm characteristics swap users and non-users

This table compares firm characteristics for firms that use swaps with firms that do not. Swap users are firms that use interest rate swaps at least once during the sample period. The stars in the last column refer to a t-test with the null hypothesis that the means for the two groups are statistically indistinguishable for the two groups. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. The data cover the period from 1994 to 2013.

	users	non users
leverage	0.163	0.103***
N	8,387	3,053
initial % floating	0.319	0.344***
N	7,918	2,166
% floating	0.335	0.344
N	7,918	2,166
Tobin's Q	2.058	2.808***
N	8,438	3,081
size	8.711	7.955***
N	8,616	3,110
cash	0.072	0.128***
N	8,460	3,076
investments	0.086	0.080***
N	7,739	2,875
profitability	0.150	0.145**
N	8,608	3,095
CF volatility	0.077	0.100***
N	8,482	3,093

Table 3
Firm characteristics summary statistic swap users only

This table reports summary statistics for firm characteristics for the sample of non-financial swap users. Swap users are firms that use interest rate swaps at least once during the sample period. The sample period is 1994 to 2013.

variable	N	mean	stdev	min	max
Panel A: All companies					
size	8,616	8.711	1.314	2.452	12.534
MtB	8,436	3.862	27.713	-678.467	1554.379
Tobin's Q	8,438	2.058	1.547	0.560	43.473
cash	8,460	0.072	0.084	0.000	0.987
leverage	8,387	0.163	0.119	0.000	0.802
investment	7,739	0.086	0.075	-0.086	0.859
CF vol	8,482	0.077	0.066	0.001	0.960
Ebitda beta	8,620	0.007	0.008	0.00	0.066
Panel B: Small companies					
size	3,722	7.595	0.889	2.452	9.241
MtB	3,657	4.101	38.174	-678.467	1,554.379
Tobin's Q	3,658	2.342	1.876	0.560	43.473
cash	3,699	0.094	0.103	0.000	0.987
leverage	3,623	0.136	0.112	0.000	0.802
investment	3,426	0.090	0.080	-0.086	.736
CF vol	3,719	0.091	0.082	0.004	0.958
Ebitda beta	3,722	0.009	0.009	0.000	0.066
Panel C: Large companies					
size	4,894	9.560	0.880	7.754	12.535
MtB	4,779	3.679	15.516	-270.390	766.007
Tobin's Q	4,780	1.841	1.194	0.692	23.582
cash	4,761	0.055	0.061	0.000	0.525
leverage	4,764	0.184	0.120	0.000	0.738
investment	4,313	0.083	0.072	-0.084	0.859
CF vol	4,763	0.067	0.048	0.001	0.958
Ebitda beta	4,898	0.006	0.006	0.000	0.066

Table 4

Predicting aggregate investment: TIV

This table shows predictive regression identical to Gilchrist and Zakrajšek (2012). Each column shows the results for a specific model. In addition to the reported explanatory variables each specification also includes a constant and p lags of the dependent variable, i.e. aggregate investment (not reported). The optimal lag length p is determined by the Bayesian information criteria (BIC). The asymptotic t-statistics reported in parentheses. In particular, for forecasting horizons $h \geq 1$, the MA(h) structure of the error term $\epsilon_t + h$ induced by overlapping observations is taken into account by computing standard errors according to Hodrick (1992). Policy uncertainty refers to the economic policy uncertainty index by Baker, Bloom, and Davis (2015). TIV refers to the Treasury implied volatility from Choi, Mueller, and Vedolin (2015). Aggregate investment is measured using real gross private domestic investment.

Aggregate Investment: Forecast horizon 4 quarters

Term Spread	-6.608	-2.735	-5.126	-6.353	-5.037	-5.473	-6.723	-6.113
	(-3.05)	(-2.08)	(-2.07)	(-2.58)	(-2.53)	(-2.22)	(-2.99)	(-2.18)
FF Rate	1.463	-1.045	0.339	1.281	0.894	1.654	1.148	0.447
	(1.0513)	(-1.31)	(0.24)	(0.84)	(0.64)	(0.96)	(0.83)	(0.26)
TIV	-2.382		-1.623	-2.097			-2.728	-2.455
	(-2.89)		(-1.83)	(-1.94)			(-2.59)	(-1.99)
GZ Spread		-4.245	-2.244					
		(-4.46)	(-2.50)					
Baa - Aaa				-2.594				-5.922
				(-0.79)				(-1.13)
Policy Uncertainty					-0.128	-0.076	-0.061	-0.078
					(-2.45)	(-2.61)	(-2.47)	(-4.16)
VIX						-0.291	0.034	0.167
						(-1.52)	(0.24)	(1.02)
adj. R^2	0.4467	0.4138	0.4766	0.4453	0.3148	0.3135	0.4446	0.4553

Table 5
Predicting real GDP: TIV

This table shows predictive regression identical to Gilchrist and Zakrajsek (2012). Each column shows the results for a specific model. In addition to the reported explanatory variables each specification also includes a constant and p lags of the dependent variable, i.e. real GDP (not reported). The optimal lag length p is determined by the Bayesian information criteria (BIC). The asymptotic t-statistics reported in parentheses. In particular, for forecasting horizons $4 \geq 1$, the MA(h) structure of the error term $\epsilon_t + 4$ induced by overlapping observations is taken into account by computing standard errors according to Hodrick (1992). Policy uncertainty refers to the economic policy uncertainty index by Bloom et al. (2015). TIV refers to the Treasury implied volatility from Choi, Mueller, and Vedolin (2015). Aggregate investment is measured using real gross private domestic investment.

Real GDP: Forecast horizon 4 quarters

Term Spread	-1.355	-0.483	-0.869	-1.077	-0.940	-1.075	-1.222	-1.097
	(-3.00)	(-1.93)	(-1.83)	(-2.51)	(-2.74)	(-2.34)	(-3.20)	(-2.42)
FF Rate	0.494	0.102	0.321	0.468	0.410	0.552	0.339	0.173
	(1.68)	(0.58)	(1.12)	(1.66)	(1.76)	(1.58)	(1.38)	(0.53)
TIV	-0.419		-0.253	-0.305			-0.614	-0.532
	(-2.56)		(-1.25)	(-1.41)			(-3.30)	(-2.37)
GZ Spread		-0.696	-0.377					
		(-3.46)	(-1.26)					
Baa - Aaa				-0.574				-1.410
				(-1.00)				(-1.23)
Policy Uncertainty					-0.024	-0.019	-0.021	-0.023
					(-2.57)	(-2.68)	(-3.35)	(-5.27)
VIX						-0.020	0.066	0.092
						(-0.52)	(1.86)	(2.55)
adj. R^2	0.3743	0.3261	0.3614	0.3458	0.3124	0.2623	0.4548	0.4756

Table 6
Interest rate uncertainty and firm-level decisions: Panel regressions

This table reports predictive panel regressions on firm-level variables such as next year's investment, cash, hedging, |% swapped|, profitability, and % floating. All specifications also include a constant and industry and year fixed effects (not reported). All but one regression specification additionally include the first lag of the dependent variable. Standard errors are clustered at the industry level.

	Invest_t+1		Cash_t+1		Hedging_t+1		|% swapped_t+1|		Profit_t+1		% float_t+1	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
TIV	-0.003	-3.61	0.005	9.64	0.005	8.43	0.003	1.72	-0.004	-6.38	-0.009	-4.35
swapuser	0.009	3.35	-0.007	-4.37	0.003	0.90			0.003	1.41	0.013	1.88
size	-0.012	-5.69	-0.005	-3.59	-0.008	-3.33	-0.010	-2.31	-0.001	-0.36	-0.010	-2.53
leverage	-0.098	-9.81	-0.014	-1.89	0.031	1.74	0.035	1.11	0.010	1.31	-0.050	-1.81
investment	0.241	9.46	-0.031	-3.47	-0.025	-1.50	-0.041	-1.28	0.010	0.82	-0.045	-1.43
long-term debt	0.007	2.09	-0.002	-0.88	-0.005	-1.21	-0.032	-2.31	0.001	0.46	-0.049	-4.95
Tobin's Q	0.002	1.99	0.001	1.00	0.006	1.58	0.003	1.01	0.006	2.86	0.000	0.09
Lagged LHS	✓		✓		✓		No		✓		✓	
adj. R^2	0.1711		0.6369		0.4432		0.028		0.6627		0.4939	
N	9,663		9,755		9,700		8,025		9,920		9,099	

Table 7
Firm-level investment: Financially constrained vs unconstrained firms

This table reports predictive panel regressions on next year's investment. All specifications also include a constant and industry and year fixed effects (not reported). Standard errors are clustered at the industry level.

	Invest_t+1		Invest_t+1		Invest_t+1		Invest_t+1		Invest_t+1	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
TIV	-0.007	-5.27	-0.003	-3.40	-0.004	-0.9	-0.006	-3.67	-0.003	-3.08
TIV*WW	-0.006	-2.75								
TIV*Z			-3.1E-05	-2.67						
TIV*HP					-0.000	-0.18				
TIV*KZ							-6.7E-05	-2.41		
TIV*Size									0.000	0.79
WW	0.066	3.03								
Z			0.000	2.86						
HP					0.014	2.2				
KZ							0.001	2.82		
swapuser	0.008	2.39	0.009	3.20	0.010	3.99	0.003	0.9	0.009	3.34
size	-0.010	-4.37	-0.012	-5.58	-0.010	-5.25	-0.009	-2.97	-0.014	-4.43
leverage	-0.112	-9.21	-0.111	-12.06	-0.103	-9.56	-0.055	-3.45	-0.098	-9.81
investment	0.217	7.26	0.219	9.60	0.238	9.59	0.249	5.84	0.241	9.45
long-term debt	0.009	2.18	0.009	2.66	0.008	2.18	0.011	2.02	0.007	2.07
Tobin's Q	0.001	1.26	0.002	1.95	0.002	1.61	0.006	3.29	0.002	1.98
adj. R^2	0.1504		0.1502		0.1781		0.1982		0.1711	
N	7,333		9,053		9,663		3,759		9,663	

Table 8
Tercile sorts of swap usage

This table reports univariate tercile sorts of % swapped along size, long-term debt, cash, and Tobin's Q (Panel A), on absolute % swapped (Panel B), and total hedging (Panel C). Total hedging is defined as sum of cash and the absolute value of the net notional amount of interest swaps outstanding scaled by book assets. The data cover the period from 1994 to 2013. The rows "High - Low" test whether "High" is statistically different from "Low". *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

	size	lt debt	cash	Tobin's Q
Panel A: % swapped				
Low	-0.0361	-0.0216	-0.0061	0.0036
Mid	0.0254	0.0282	0.0137	0.0230
High	0.0344	0.0311	0.0473	0.0243
Total	0.0139	0.0143	0.0144	0.0163
High - Low	0.0736***	0.0527***	0.0533***	0.0207***
Panel B: absolute % swapped				
Low	0.0948	0.0947	0.0712	0.0656
Mid	0.0862	0.0813	0.0914	0.0894
High	0.0749	0.0749	0.0939	0.0983
Total	0.0839	0.0832	0.0841	0.0832
High - Low	0.0199***	0.0197***	0.0227***	0.0327***
Panel C: total hedging				
Low	0.1180	0.1092	0.0373	0.0717
Mid	0.0984	0.0808	0.0799	0.0926
High	0.0789	0.0914	0.2020	0.1270
Total	0.0963	0.0930	0.0963	0.0957
High - Low	0.0391***	0.0177***	0.1648***	0.0553***

Table 9
Double sorts of % swapped

This table reports unconditional double sorts of % swapped along Tobin's Q and leverage (Panel A) and size and leverage (Panel B). The data covers the time period from 1994 to 2013. The columns and rows labeled "High - Low" test whether "High" is statistically different from "Low". *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Panel A: Leverage & Tobin's Q

	Leverage				
Q	Low	Mid	High	Total	Low-High
Low	0.0205	0.0120	-0.0036	0.0019	0.0242**
Mid	0.0374	0.0326	-0.0025	0.0238	0.0400***
High	0.0376	0.0362	-0.0010	0.0355	0.0386**
Total	0.0363	0.0286	-0.0032	0.0026	
High - Low	0.0171	0.0242***	0.0348		

Panel B: Leverage & Size

	Leverage				
Size	Low	Mid	High	Total	High-Low
Small	-0.0063	-0.0072	-0.0179	-0.0094	0.0225
Mid	0.0483	0.0377	-0.0039	0.0254	0.0521***
Large	0.0850	0.0545	0.0050	0.0413	0.0800***
Total	0.0363	0.0286	-0.0032	0.0200	
Large - Small	0.0913***	0.0617***	0.0229***		

Table 10
Double Sorts of absolute % swapped

This table reports unconditional double sorts of absolute % swapped along Tobin's Q and leverage (Panel A) and along size and leverage (Panel B). The data covers the time period from 1994 to 2013. The columns and rows labeled "High - Low" test whether "High" is statistically different from "Low". *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Panel A: Leverage & Tobin's Q

	Leverage				
Q	Low	Mid	High	Total	Low-High
Low	0.0769	0.0729	0.0621	0.0657	0.0148
Mid	0.0949	0.0862	0.0828	0.0873	0.0121
High	0.0950	0.0916	0.0848	0.0936	0.0102
Total	0.0936	0.0845	0.0687	0.0819	
High - Low	0.0181	0.0187***	0.0227**		

Panel B: Leverage & Size

	Leverage				
Size	Low	Mid	High	Total	High-Low
Small	0.1047	0.1022	0.0932	0.1011	0.0115
Mid	0.0909	0.0834	0.0838	0.0857	0.0071
Large	0.0899	0.0815	0.0489	0.0699	0.0410***
Total	0.0936	0.0845	0.0687	0.0819	
Large - Small	0.0148	0.0207***	0.0443***		

Table 11
Double Sorts of total hedging

This table reports unconditional double sorts of total hedging along Tobin's Q and leverage (Panel A) and size and leverage (Panel B). The data covers the time period from 1994 to 2013. The columns and rows labeled "High - Low" test whether "High" is statistically different from "Low". *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Panel A: Leverage & Tobin's Q

	Leverage				
Q	Low	Mid	High	Total	High - Low
Low	0.1082	0.0812	0.0642	0.0717	0.0440***
Mid	0.1126	0.0902	0.0898	0.0954	0.0228***
High	0.1270	0.1247	0.1198	0.1261	0.0072
Total	0.1222	0.0976	0.0737	0.0979	
High - Low	0.0188**	0.0435***	0.0556***		

Panel B: Leverage & Size

	Leverage				
Size	Low	Mid	High	Total	High-Low
Small	0.1350	0.1122	0.0937	0.1179	0.0412***
Mid	0.1183	0.0939	0.0802	0.0963	0.0381***
Large	0.1051	0.0860	0.0565	0.0791	0.0486***
Total	0.1222	0.0976	0.0737	0.0979	
Large - Small	0.0299***	0.0262***	0.0373***		

Table 12
Double sorts of absolute % swapped

Panel A reports univariate sorts of absolute % swapped along terciles of 5 year credit spread, 5 year expected probability of default (EPD), size, and WW-index. The rest of the table reports unconditional double sorts of absolute % swapped along size and credit spread (Panel B) and the WW-index and credit spread (Panel C). The data covers the time period from 1994 to 2013. The columns and rows labeled "High - Low" test whether "High" is statistically different from "Low". *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Panel A: Univariate Sorts

	1	2	3	Total	Low - High
Credit Spread	0.1193	0.0904	0.0783	0.0961	0.0411***
EPD	0.0961	0.0911	0.0834	0.0902	0.0127***
Size	0.0948	0.0862	0.0749	0.0839	0.0199***
WW-Index	0.0808	0.0866	0.0906	0.0855	0.0098*

Panel B: Size & Credit Spread

	Credit Spread				
Size	Low	Mid	High	Total	Low - High
Low	0.1611	0.1055	0.09438	0.1167	0.0668**
Mid	0.1148	0.0939	0.0930	0.0997	0.0218*
High	0.1144	0.0848	0.0582	0.0884	0.0562***
Total	0.1193	0.0904	0.0783	0.0961	
Low - High	0.0467**	0.0207	0.0362***		

Panel C: WW-Index & Credit Spread

	Credit Spread				
WW-Index	Low	Mid	High	Total	Low - High
Low	0.1093	0.0745	0.0737	0.0877	0.0357***
Mid	0.1257	0.0877	0.0784	0.0979	0.0472***
High	0.1438	0.1040	0.0882	0.1056	0.0556**
Total	0.1186	0.0837	0.0789	0.0942	
High - Low	0.0344	0.0295**	0.0145		

Table 13
Double sorts of absolute % swapped

This table reports unconditional double sorts of absolute % swapped along size and the expected probability of default (EPD) (Panel A) and the WW-index and the expected probability of default (Panel B). The data covers the time period from 1994 to 2013. The columns and rows labeled "High - Low" test whether "High" is statistically different from "Low". *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Panel A: Size & EPD

	EPD				
Size	Low	Mid	High	Total	Low - High
Low	0.1031	0.1021	0.0992	0.1013	0.0039
Mid	0.0948	0.0877	0.0866	0.0897	0.0081
High	0.0912	0.0757	0.0593	0.0770	0.0326***
Total	0.0961	0.0888	0.0834	0.0894	
Low - High	0.0112	0.0264***	0.0400***		

Panel B: WW-Index & EPD

	EPD				
WW-Index	Low	Mid	High	Total	Low - High
Low	0.0910	0.0828	0.0839	0.0862	0.0070
Mid	0.1034	0.0903	0.0882	0.0946	0.0153
High	0.1036	0.1056	0.0888	0.0979	0.0147
Total	0.0982	0.0916	0.0871	0.0924	
High - Low	0.0126	0.0229**	0.0049		

Table 14
Panel regressions credit risk: 5y credit spread

This table reports pooled panel regressions of firms' monthly average of the daily 5 year Credit Default Spreads (CDS) on initial % floating, %floating, |% swapped|, size, leverage, investment, cash, profitability, Tobin's Q and cash flow volatility. All regressions include industry and year fixed effects. t-statistics are clustered at the industry level and reported in parentheses. Data sample runs from 2002 to 2012.

	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
initial % floating	.0191	(1.88)				
% floating			.0081	(0.99)		
|% swapped|					-.0205	(-2.25)
size	-.0006	(-0.19)	-.0005	(-0.16)	-.0002	(-0.07)
leverage	.0966	(2.59)	.1001	(2.73)	.1014	(2.62)
investment	-.0393	(-1.52)	-.0356	(-1.37)	-.0355	(-1.28)
cash	.0615	(1.67)	.0591	(1.58)	.0713	(1.75)
profitability	-.1824	(-2.79)	-.1826	(-2.77)	-.1932	(-2.64)
Tobin's Q	.0066	(1.86)	.0069	(1.89)	.0075	(1.60)
CF volatility	.0806	(2.55)	.0850	(2.57)	.0953	(2.55)
R^2	.1069		.1032		.1022	
N	2,926		2,926		2,947	

Table 15

Panel regressions default risk: 5y expected probability of default

This table reports pooled panel regressions of firms' monthly expected probability of default (EPD) on initial % floating, %floating, |% swapped|, size, leverage, investment, cash, profitability, Tobin's Q and cash flow volatility. All regressions include industry and year fixed effects. t-statistics are clustered at the industry level and reported in parentheses. Data sample runs from 1994 to 2013.

Panel A: All firms

	coefficient	t-stat	coefficient	t-stat	coefficient	t-stat
initial % floating	.0054	(2.46)				
% floating			.0030	(1.40)		
|% swapped|					-.0068	(-2.58)
size	.0000	(0.03)	-.0001	(-0.22)	-.0003	(-0.45)
leverage	.1028	(10.32)	.1029	(10.21)	.1030	(9.90)
investment	-.0043	(-0.51)	-.0034	(-0.40)	-.0050	(-0.58)
cash	.0077	(1.22)	.0061	(0.97)	.0047	(0.67)
profitability	-.0629	(-3.98)	-.0627	(-3.95)	-.0590	(-3.70)
Tobin's Q	.0000	(0.08)	.0000	(0.08)	-.0001	(-0.13)
CF volatility	.0242	(2.78)	.0248	(2.75)	.0248	(3.02)
R^2	.2275		.2260		.2304	
N	7,089		7,089		6,261	

Panel B: Small and large firms

	small firms		*large firms*	
	coefficient	t-stat	coefficient	t-stat
|% swapped|	-.0083	(-2.92)	-.0077	(-1.96)
size	-.0010	(-1.01)	.0036	(3.20)
leverage	.1162	(7.08)	.1015	(6.24)
investment	-.0069	(-0.57)	.0013	(0.12)
cash	-.0031	(-0.46)	.0173	(1.51)
profitability	-.0579	(-2.69)	-.0658	(-5.36)
Tobin's Q	.0005	(0.66)	-.0008	(-0.071)
CF volatility	.0243	(2.54)	.0406	(3.57)
R^2	.2651		.2126	
N	2,891		3,370	

Table 16
Calibration

This table summarizes our calibration used to solve and simulate our model. All values are annual.

Description	Parameter	Value
Cash holding costs	ζ	0.006
Interest rate persistence	ρ_r	0.86
Interest rate volatility	σ_r	0.023
Risk aversion	γ_0	10
Time-varying risk aversion	γ_1	-120
Persistence of aggregate shock	ρ_x	0.88
Volatility of aggregate shock	σ_x	0.03
Persistence of idiosyncratic shock	ρ_z	0.81
Volatility of idiosyncratic shock	σ_z	0.29
Capital share	α	0.65
Fixed costs of production	f	0.03
Corporate tax rate	τ	0.14
Bankruptcy costs	ξ	0.2
Fixed equity issuance costs	λ_0	0.06
Fixed debt adjustment costs	ϕ_0	0.006
Proportional debt adjustment costs	ϕ_1	0.02
Swap issuance costs	ψ	0.012

Table 17
Moments

This table reports unconditional moments of corporate policies and interest rates generated by the model. All moments are annual.

Moment	Data	Model
Average market leverage	0.28	0.31
Dispersion in market leverage	0.41	0.35
Frequency of equity issuances	0.07	0.08
Average new equity-to-asset ratio	0.12	0.10
Average market-to-book ratio	2.25	1.84
Average profitability	0.15	0.13
Dispersion in profitability	0.12	0.09
Average cash-to-asset ratio	0.09	0.11
Short-rate volatility	0.023	0.023
One year credit spread	0.007	0.008
Ten year credit spread	0.013	0.012
Annual default rate	0.01	0.01

Table 18
Correlations

This table reports unconditional correlations between firm characteristics generated by the model.

size	1.00					
leverage	0.45	1.00				
long-term debt	0.83	0.65	1.00			
cash	-0.71	-0.67	-0.64	1.00		
Tobin's Q	-0.39	-0.56	-0.47	0.51	1.00	
% floating	-0.63	-0.58	-0.61	0.56	0.65	1.00

Table 19
Swap moments

This table reports unconditional moments of swap usage measures generated by the model. All moments are annual.

Moment	Data	Model
Fraction of swap users	0.73	0.71
Absolute percentage swapped	0.065	0.058
Net percentage swapped	0.011	0.015

Table 20
Tercile sorts of swap usage: Model

This table reports univariate tercile sorts of % swapped along size, long-term debt, cash, and Tobin's Q (Panel A) and of absolute % swapped (Panel B), from model simulations.

	size	lt debt	cash	Tobin's Q
Panel A: % swapped				
Low	-0.013	-0.014	-0.012	-0.014
Mid	0.009	0.011	0.010	0.008
High	0.023	0.022	0.021	0.025
Total	0.019	0.019	0.019	0.019
Panel B: absolute % swapped				
Low	0.083	0.082	0.070	0.068
Mid	0.075	0.076	0.075	0.075
High	0.069	0.069	0.081	0.083
Total	0.076	0.076	0.076	0.076

5 Figures

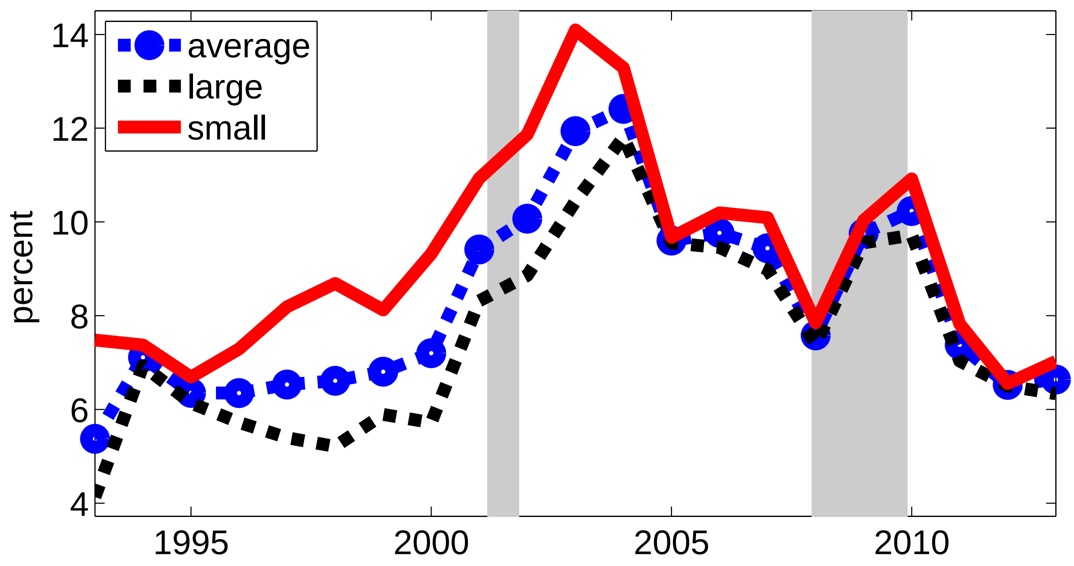


Figure 1. Swap usage

This figure plots |% swapped|for the whole sample, large, and small firms. Gray bars indicate NBER recessions. Data is annual and runs from 1994 to 2013.

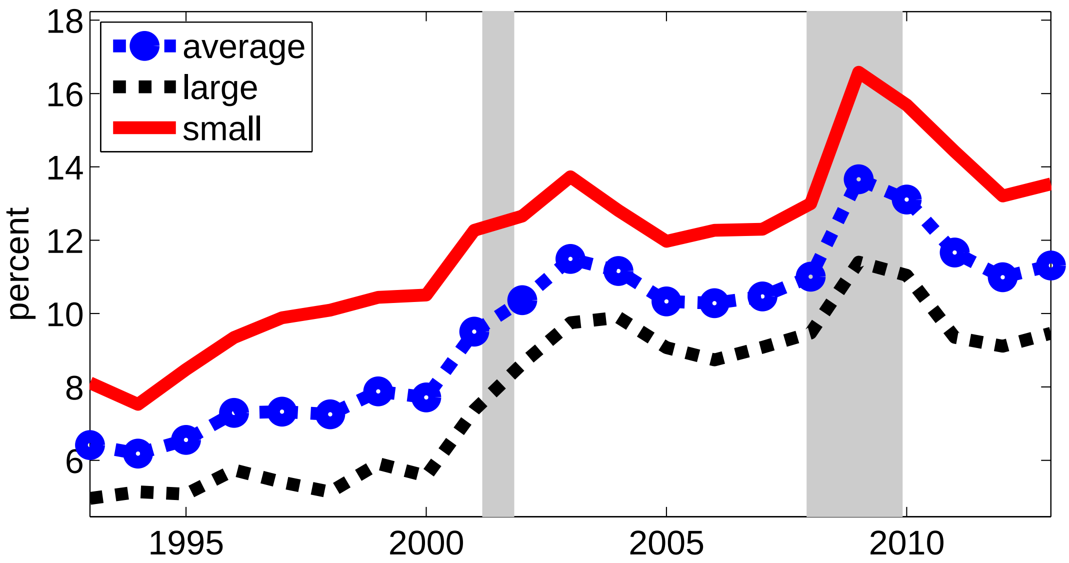


Figure 2. Total hedging

This figure plots total hedging for the whole sample, large, and small firms. Gray bars indicate NBER recessions. Data is annual and runs from 1994 to 2013.

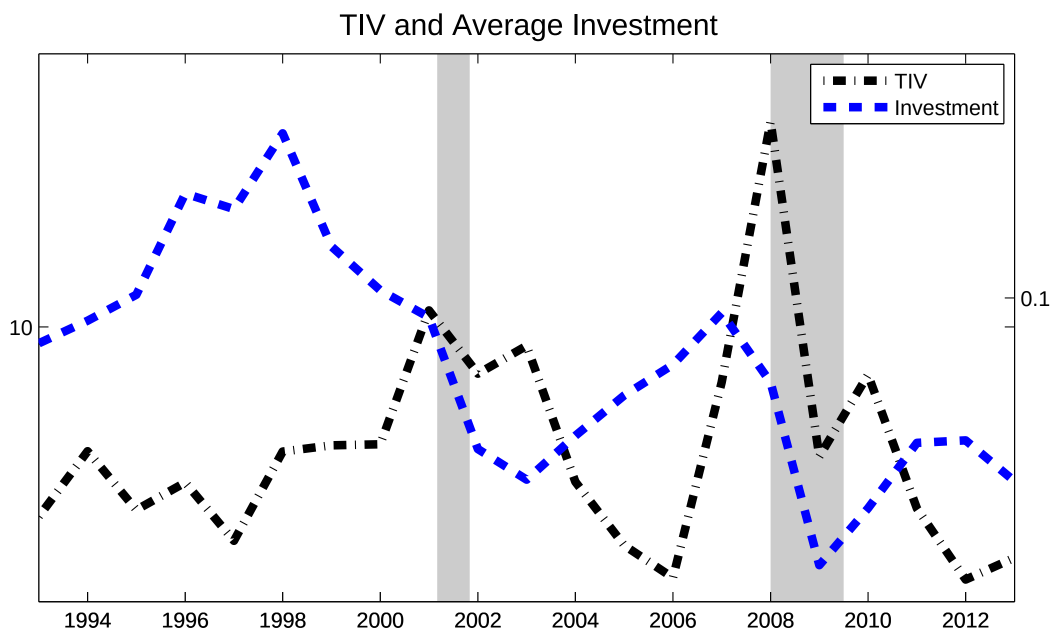


Figure 3. TIV and investment

This figure plots the Treasury implied volatility (TIV) and average investment time series for the period from 1993 to 2013. Investment for a specific firm is calculated as the sum of capital expenditure and acquisitions scaled by book assets. Average investment is simply the average of investment across all our sample firms in a given year.

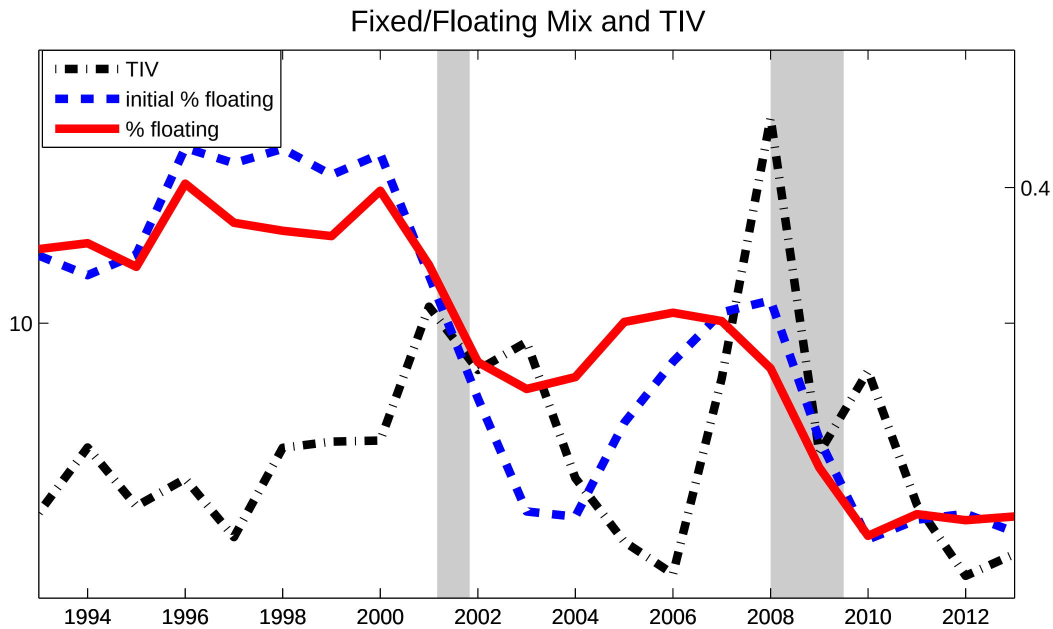


Figure 4. TIV and the fix-floating mix

This figure plots the TIV, initial % floating and % floating time series. Again, the latter two variables are averages across all sample firms available. A value of 10% for initial % floating and 5% for % floating corresponds to a firm which swaps 50% of its floating debt to fixed debt (via cash flow swaps).

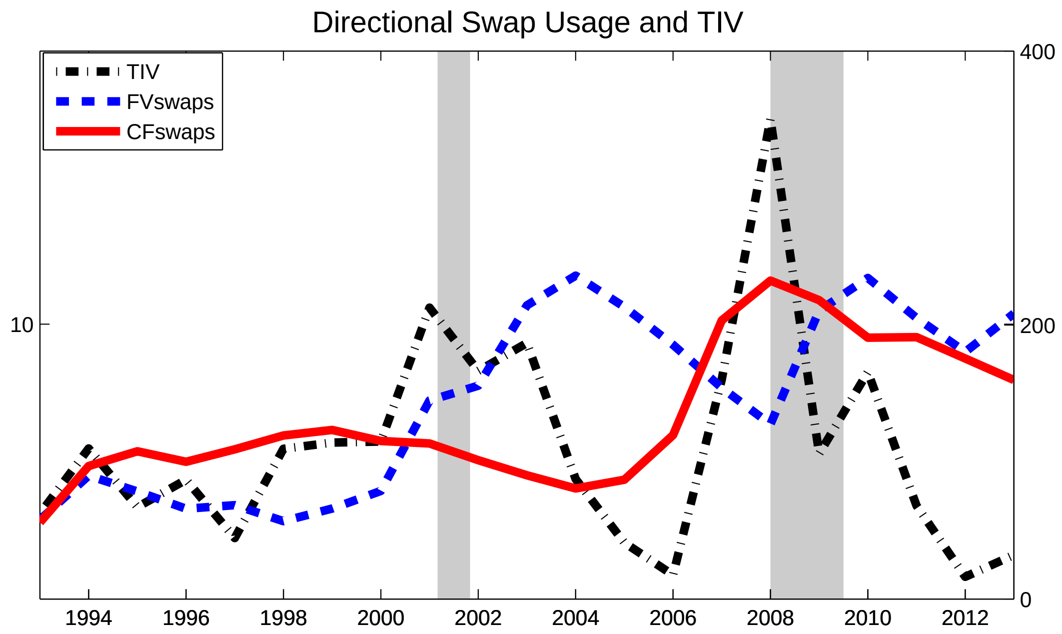
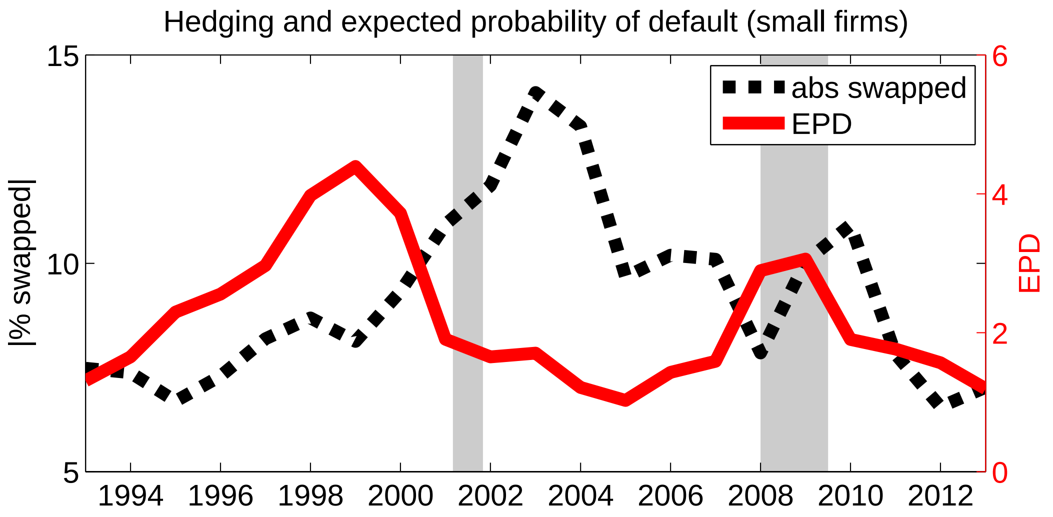


Figure 5. TIV and directional swap usage

This figure plots the annual time series of TIV, average cash flow swap and average fair value swap notionals. The swap notionals are calculated by averaging the corresponding notionals of every swapuser in our sample in a given year. Reminder: A cash flow swap transforms floating into fixed rate debt, whereas a fair value swap does the opposite.



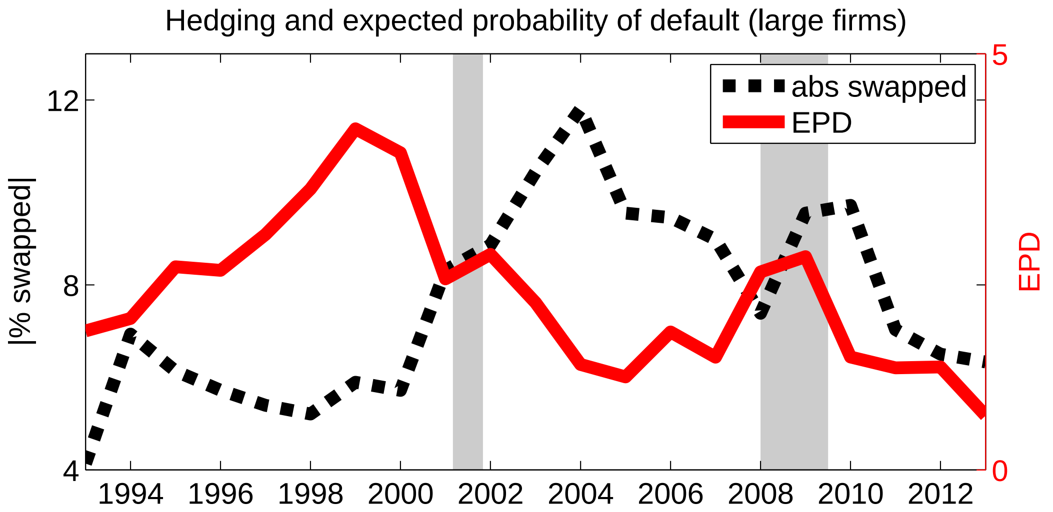


Figure 6. Hedging and expected default probability

This figure plots average expected default probabilities for small firms (upper panel) and large firms (lower panel) together with the absolute percentage of outstanding debt swapped. Gray bars indicate NBER recessions. Data is annual and runs from 1994 to 2013.

6 Appendix

Starting in 1990, the Statement of Financial Accounting Standards (SFAS) 105 required disclosures about the amounts, nature, and terms of financial derivative instruments with off-balance-sheet risk of accounting loss, which include interest rate swaps. These reporting standards allow us to determine whether 1) a firm uses interest rate swaps at all, 2) swaps net fixed-for-floating or floating-for-fixed at the end of a fiscal year. Given our interest in the fraction of a firm's debt that is swapped to floating (respectively fixed) we record only debt-related interest rate swaps which are effective at the end of each fiscal year. In our data collection we closely follow Chernenko and Faulkender (2011) and exclude swaps related to non-debt items such as investments, operating leases, or preferred stock from our analysis. Moreover, forward-starting interest swaps which are sometimes used to hedge future anticipated debt issuances are also disregarded. Some firms also engage in foreign exchange swaps. These swaps are only included in the analysis if they modify the nature of the companies' interest rate exposure by changing floating debt to fixed or the other way around.

The relevant information about interest rate swaps outstanding at the end of the fiscal year is most commonly found in the sections "7A. Quantitative and Qualitative Disclosures about Market Risk", "9. Long-term Debt/Borrowings", or "12. Derivatives" of the companies' annual reports, i.e. 10-K filings. In order to get a precise measure of a firm's debt composition in a given year, we additionally hand-collect the amount of floating-rate long-term debt before consideration of the effects from outstanding interest rate swaps. Information regarding outstanding floating-rate long-term debt is found in the long-term debt section of the 10-K filings. Most companies include a table reporting principal amounts of long-term debt. In order to classify the single positions as either fixed- or floating-rate debt requires some degree of subjectivity. Classifying the single positions, we again follow the procedure proposed by Chernenko and Faulkender (2011). We are rather conservative in classifying long-term debt as floating, i.e. if it is unclear whether a table entry refers to fixed- or floating-debt we treat it as fixed. We also read the footnotes related to every single entry to make sure we do not make any evadable mistakes. Our default assumptions are that:

- commercial paper, credit facilities, and short-term debt classified as long-term are floating rate;
- bank loans are floating rate;
- bonds, industrial revenue bonds, debentures, and notes are fixed rate;
- capital leases are treated as fixed rate;
- "other" is treated as fixed rate.

To verify the reliability of our hand-collected amount of floating-rate debt, we compare the percentage of long-debt with a floating interest rate with the Compustat variable "Long-Term Debt Tied to Prime" (DLTP). The correlation between the two variables is very high (0.8745). However, the Compustat variable is missing for 35.64% of our firm-year observations in our sample. Moreover, it is not a priori clear whether the effects of interest rate swaps are in- or excluded in the Compustat variable.[2]

[2] In fact, it appears that interest rate swaps are included in one year and excluded in another year for some companies.