Interest Rate Uncertainty, Hedging, and Real Activity*

Lorenzo Bretscher
LSE†

Lukas Schmid
Duke‡

Andrea Vedolin
LSE§

Abstract

Uncertainty about the future path of interest rates is associated with a significant slowing of future economic activity both at the aggregate and firm level. Using a novel data set on firms' interest rate swap usage, we find that 1) interest rate risk management helps firms attenuate the adverse effects of interest rate uncertainty on investment and 2) 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.

Keywords: interest rate risk, monetary policy uncertainty, risk management, interest rate swaps, financial frictions, corporate investment

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

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

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

1 Introduction

All eyes were on the December 2015 Federal Open Market Committee meeting when Chairman Yellen announced the first interest rate hike in nearly a decade. While the target rate increase has been anticipated by many market participants, the announcement immediately raised questions about the timing of future interest-rate changes. Market expectations about the Federal Reserve's policy rate not only involve the future path of that rate but also the uncertainty surrounding that path. In the past, many policymakers and market pundits have argued that the uncertainty about the Fed's actions can be harmful for the economy. These recent events highlight the importance of a better understanding of whether and how interest rate uncertainty affects economic activity.

Figure 1 depicts a proxy of interest rate uncertainty, TIV (Treasury implied volatility), an implied volatility index from Treasury future options, akin to the VIX in the equity market, together with two other common uncertainty proxies: the economic policy index of Baker, Bloom, and Davis (2015) (upper panel) and the VIX, a measure of equity market uncertainty (lower panel). We note that while all series feature a strong counter-cyclical component, that is, they increase during recessions and decrease during booms, the interest rate uncertainty proxy displays distinct spikes which are mainly due to events related to debt markets or more generally monetary policy. For example, the interest rate uncertainty index jumps many times between 2001 and 2003, a period during which the Federal Reserve cut the target Federal funds rate in several meetings. Increased monetary policy uncertainty has also been a key topic of policymakers during this period as emphasized, for example, in Chairman Greenspan's (2003) Jackson Hole speech.[1] Similarly, elevated interest rate uncertainty since 2010 is mainly due to market participants' uncertainty about how and whether the Fed's unconventional monetary policy affects the economy and about the Fed's tapering. This paper provides novel insights into the relationship between interest rate uncertainty and economic activity both at the aggregate and on the firm level.

[Insert Figure 1 here.]

[1] Greenspan's opening remarks are: "Uncertainty is not just an important feature of the monetary policy landscape; it is the defining characteristic of that landscape."

Intuitively, significant interest rate uncertainty impacts estimates of the future cost of capital and thus firms' financing conditions and investment. In contrast to broader measures of uncertainty, such as generic policy uncertainty, fluctuations in interest rates can be hedged through the derivatives market through interest rate swaps. In this paper, we start by documenting the strong predictive power of various proxies for interest rate uncertainty for real activity. By means of a novel, comprehensive, and hand-collected data set on interest rate swap usage, we then examine to what extent corporations hedge interest rate risk using swaps. Finally, we interpret our empirical findings through the lens of a dynamic model of corporate interest rate risk management in the presence of investment and financing frictions.

In the data, we find that uncertainty about the future path of interest rates is associated with a significant slowing of future economic activity. Empirical proxies of interest rate uncertainty, such as TIV, a dispersion measure from forecasts of the three-month Treasury yield, and realized volatility measures of short-term yields, negatively predict future aggregate investment. These results are robust to inclusion of standard business cycle indicators, well known business cycle predictors such as credit spreads, as well as broader uncertainty measures such as the VIX, the economic policy uncertainty measure by Baker, Bloom, and Davis (2015) or the financial uncertainty index by Jurado, Ludvigson, and Ng (2015). Notably, our preferred interest uncertainty measure drives out standard business cycle predictors such as credit spreads. The estimated coefficients are not only statistically significant but also economically meaningful. For example, for any one standard deviation change in interest rate uncertainty, there is on average a 0.4 standard deviation change in the growth rate of aggregate investment which translates to an average $52 billion movement.

We further dissect the empirical evidence on the links between interest rate uncertainty and corporate investment at the firm level. This not only allows us to control more accurately for investment opportunities, but also, and perhaps more interestingly, by examining cross-sectional heterogeneity to get a first glimpse of the mechanisms underlying our findings. This is important, as the negative relation between interest rate uncertainty and corporate investment is potentially consistent with a variety of explanations. On the one hand, the real options literature has long emphasized that elevated uncertainty can lead corporations to delay investment projects when these are partially irreversible. This discount rate effect certainly may also apply to interest rate related uncertainty. On the other hand, uncertainty about interest rate payments associated with debt financed investment expenditures may also inhibit exercising growth options - a cash flow effect. Cross-sectionally, we find that the negative link between interest rate uncertainty and future investment is stronger in more financially constrained and levered firms, and insignificant in a sample of zero-leverage firms, thus providing suggestive support for a cash flow risk channel.

The distinction between discount rate and cash flow channels is relevant in that corporations can hedge uncertainty about future interest payments in the swap market. Using a large cross-section of hand-collected data on publicly traded firms' interest rate risk hedging over the past twenty years, we document that interest rate risk management indeed helps firms attenuate adverse effects of interest rate uncertainty on investment. However, we also find evidence for substantial cross-sectional differences in swap usage. While firms tend to be fixed rate payers on average, a finding in line with earlier research (see e.g., Chernenko and Faulkender (2011)), we document a significant and robust negative relationship between firm size and hedging activity. Relatedly, and perhaps more notably, 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. While this is consistent with perceived intuition, originating in Froot, Scharfstein, and Stein (1993), that risk management may further enhance value for constrained firms as it allows them to better take advantage of investment opportunities and avoid liquidity shortfalls, recent research in Rampini, Sufi, and Viswanathan (2013) and Rampini, Viswanathan, and Vuillemey (2015) challenges this view in case of the airline industry and for U.S. financial institutions. Similar to their findings, we confirm that distressed firms, as identified by high default probabilities and credit spreads, hedge their exposure only little. One potential explanation 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., Farre-Mensa and Ljungqvist (2015)), 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.

While we find the documented empirical links between interest rate uncertainty, risk management, and real activity to be revealing, they do not formally go far beyond suggestive correlations in absence of a valid instrument. To interpret our findings, we thus develop a dynamic model of corporate interest rate risk management in the presence of interest rate uncertainty. The result is a quantitative model of a cross-section of firms which finance investment with defaultable debt and equity in the presence of aggregate interest rate risk, interest rate volatility risk, and financial frictions. Calibration allows us to gauge the real impact of both shocks to the level and to the conditional volatility of interest rates, such as elevated uncertainty about the future path of interest rates, through the lens of our model.

In the model, as in practice, firms can engage in risk management. In the frictionless world of Modigliani and Miller (1958), hedging is irrelevant for the firm. With financial frictions, risk management can create value 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. 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. In other words, swap contracts allow firms to transfer resources across future states and thus emerge as a contingent risk management instrument, while cash reallocates current funds to future states symmetrically.

The model endogenously generates rich cross-sectional patterns about investment, capital structure, default risk, and risk management, that are quantitatively in line with the empirical evidence. In particular, our data set allows us to calibrate the model tightly to corporate interest rate risk management practices. Our model-based estimates then suggest that a positive innovation to interest rate volatility generates adverse effects on corporate investment in similar orders of magnitudes as positive shocks to interest rate levels. Through the lens of the model, our empirical findings are thus consistent with an economic environment in which adverse movements in interest rate uncertainty are a source of slowdowns in economic activity.[2] To the extent that interest rate uncertainty reflects uncertainty about the future stance of monetary policy, effective forward guidance that reduces uncertainty about the future path of the short-term interest rate thus emerges as a critical aspect of monetary stabilization policy. Notably, this perspective arises in a setting where firms endogenously engage in a realistic amount of interest risk management through swaps.

The rest of the paper is organized as follows. After the literature review, we describe the data and present our main empirical findings. Section 3 presents a model of dynamic risk management together with a calibration. Finally, we conclude in Section 4.

Literature review: Our paper contributes to several strands of the literature. First, a growing literature in macroeconomics and finance examines empirically and theoretically the links between various measures of uncertainty and real activity. A non-exhaustive list of classic and recent papers reporting a negative relationship between uncertainty and real activity at either the aggregate or the firm level includes Leahy and Whited (1996), Bloom, Bond, and Van Reenen (2007), Bloom (2009), Gilchrist, Sim, and Zakrajšek (2014), Kim and Kung (2014), and Ludvigson, Ma, and Ng (2015). In contrast to these papers, to the best of our knowledge, our analysis is the first to focus exclusively on interest rate related uncertainty, both empirically and theoretically.

To the extent that interest rate uncertainty is related to uncertainty about monetary policy, our paper is more specifically related to the emerging literature on the economic implications of policy uncertainty. Recent papers examining that link include Pástor and Veronesi (2012,

[2] This is consistent with recent empirical evidence in Ludvigson, Ma, and Ng (2015), which supports the notion that uncertainty about financial markets are likely a source of fluctuations, rather than a response.

2013), Croce, Kung, Nguyen, and Schmid (2012), Brogaard and Detzel (2015), and Kelly, Pástor, and Veronesi (2016). In contrast to these contributions, we investigate the real effects of monetary policy uncertainty. In that respect, our work is closer to Gulen and Ion (2015) who study the effect of policy uncertainty, as measured by the Baker, Bloom, and Davis (2015) index, on firm level investment. Similar to us, they document a negative relationship between policy uncertainty and the incentive to delay investments which they relate to the degree of irreversibility of firm's investments. Our results are different from theirs along several dimensions. First, on the empirical side, we show that interest rate uncertainty affects investment even when we condition on more general measures of uncertainty, such as the policy uncertainty index or the VIX. Second, interest rate risk can be hedged through derivative instruments and we show how firms make use of this option in a large cross-section. Third, theoretically, we propose a quantitative model that emphasizes a different channel which is based on the premise that firms face investment and financing frictions.

Since interest rate uncertainty can be hedged, in contrast to broader notions of policy uncertainty, our paper is related to the literature on hedging and risk management. Classic theoretical contributions include Stulz (1984), Smith and Stulz (1985), Froot, Scharfstein, and Stein (1993), Leland (1998), and Morellec and Smith (2007). In these papers, financing frictions are exogenously given and they show how corporate cash and risk management can create value by relaxing financial constraints.

Several papers empirically study firms' hedging in commodity markets. For example, Rampini, Sufi, and Viswanathan (2013) examine fuel hedging in the airline industry and Doshi, Kumar, and Yerramilli (2015) study the effect of commodity price uncertainty on firms' hedging behavior and investments in the upstream oil and gas industry. Similar to us, the latter reports a negative link between uncertainty and investment, however, the relationship seems the most pronounced in small firms.

More recently, a literature on risk management in dynamic models has emerged. On the theoretical side, Rampini and Viswanathan (2010, 2013) build dynamic models 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. In the models of Bolton, Chen, and Wang (2011, 2012), 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. In its emphasis on the effects of stochastic interest rates on corporate investment, our paper is also related to the theoretical analysis in Wang, Wang, and Yang (2013).

A small number of recent papers has also examined interest rate related risk management practices, both empirically and theoretically. Similar to us, Chernenko and Faulkender (2011) empirically explore the cross-section of swap usage. Different from us, they investigate differences between hedging and speculative motives underlying swap usage and do not consider real effects, neither empirically nor theoretically.

In contemporaneous and complementary work, Vuillemey (2015) develops a quantitative dynamic model of bank interest rate risk management. Similarly, Rampini, Viswanathan, and Vuillemey (2015) empirically study hedging for U.S. financial institutions and document a positive relation between net worth and hedging. On a related note, Begenau, Piazzesi, and Schneider (2015) develop a novel approach to estimate banks' risk exposure due to their interest rate derivative positions. In contrast to that line of work, our empirical and quantitative work examines swap usage of non-financials.

Regarding interest rate risk management using swaps and its real effects, our paper is related to the general equilibrium model in Jermann and Yue (2014). 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.

More broadly, our quantitative work is related to the large literature on dynamic capital structure and investment, starting with Gomes (2001) and Hennessy and Whited (2005, 2007). More recent papers emphasizing risk management through cash holdings include Gamba and Triantis (2008), Riddick and Whited (2009), Hugonnier, Malamud, and Morellec (2015), Nikolov, Schmid, and Steri (2014), and Eisfeldt and Muir (2015), while Bhamra, Kuehn, and Strebulaev (2011) and Begenau and Salomao (2015) examine financing decisions in the presence of aggregate risk, similar to us.

2 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 quantitatively examine the cross-sectional and time series determinants of interest rate risk management. Finally, we show that firms' hedging policies significantly affect the interaction between interest rate uncertainty and corporate investment.

2.1 Data

We use data from several data sources starting in 1994 and ending in 2014.

Interest Rate Uncertainty: Our primary measure of interest rate uncertainty is Treasury implied volatility (TIV henceforth), as constructed in Choi, Mueller, and Vedolin (2015). TIV is akin to the well-known VIX index which is calculated from one-month equity index options on the S&P500. Similarly, TIV is a measure of implied volatility from one-month options written on thirty-year Treasury bond futures. As robustness, we alternatively use the MOVE index, the Bank of America-Merrill Lynch volatility index from Treasury options, realized volatility of a one-year constant maturity Treasury yield, and the interquartile range from survey forecasts of the three-month Treasury yield from the Philadelphia Federal Reserve.[3] Previous literature has demonstrated a link between policy uncertainty as proxied by Baker, Bloom, and Davis (2015) and investment. To gauge the impact of interest rate uncertainty above and beyond market or policy uncertainty, we run the following regression:

$$\mathrm{TIV}_t = c + b \text{ policy uncertainty}_t + e_t,$$

and use the residuals from this regression, $\hat{e}_t$, as an additional control.[4] We proceed similarly with the Jurado, Ludvigson, and Ng (2015) financial uncertainty index which is calculated from a cross-section of 147 financial variables.

[3] We refer to the online appendix for a detailed sensitivity analysis using different interest rate uncertainty proxies, sub sample analysis, as well as further empirical results.

[4] Overall the unconditional correlation between TIV and the policy uncertainty index is below 30%.

Other uncertainty proxies and aggregate variables: We use different macro-economic variables such as GDP growth, the level of the Federal funds rate, and the term spread, defined as the difference between the ten-year and three-month constant-maturity Treasury yields. As two measures of aggregate credit risk, we employ the Moody's Baa-Aaa credit spread and the Gilchrist and Zakrajšek (2012) credit index which is calculated from a large cross-section of firm level corporate bonds traded in the secondary market. We also make use of a more "general" or financial market uncertainty proxy, which is the VIX.

Hedging variables: We start with a sample consisting of the largest 1,600 firms in Compustat.[5] 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.[6] 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 net notional amount of interest swaps outstanding as a percentage of the firm's total debt and indicates 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. Using these different filters leaves us with 17,631 firm-year observations.

Firm determinants: To study determinants of firms' hedging activity, we also gather 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

[5] We cut our sample at 1,600 firms as very small firms make little use of financial derivatives but rather adjust their interest rate risk exposure through credit lines with banks (see e.g., Vickery (2008)).

[6] We defer a detailed discussion of how we collect and filter the interest rate swap usage data to the online appendix.

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.

Financial constraint measures: Following Whited and Wu (2006), we construct a financial constraints index, henceforth WW index, which is based on the coefficients from a structural model. More specifically, a firm is defined to be financially constrained 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. Other popular indices that we use are Altman (1968)'s Z score, the Kaplan and Zingales (1997), and Hadlock and Pierce (2010) indices.

Financial distress: 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 2014 from Markit. In our analysis, we merge the monthly average of the five-year credit spreads in the respective fiscal-year-end month for each company in every year. We focus on five-year credit spreads as they are the 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 2014. To allow for a comparison of the results, we also focus on the five-year EPD in the respective fiscal-year-end month for each company in every year.

2.2 *Interest rate uncertainty and economic activity*

We begin our empirical analysis by investigating the relationship between interest rate uncertainty and real activity. We first document links at the aggregate level and then further dissect them at the firm level, followed by an examination of cross-sectional heterogeneity.

2.2.1 *Aggregate results*

As a preliminary exploration of our data, we plot in Figure 2a average firm level investment together with our proxy of interest rate uncertainty. Two observations are noteworthy. First, the comovement between the two variables is strongly negative. Second, movements in uncertainty appear to lead movements in aggregate investment: As TIV rises, aggregate investment falls with some delay.

More formally, we now document the relationship between aggregate investment and interest rate uncertainty by means of predictive regressions using a one-year (four-quarter) horizon. We use TIV along with a number of relevant forecasting variables to predict aggregate investment. More specifically, we run the following regression:

$$\Delta \mathrm{I}_{t+4} = \alpha + \beta \, \mathrm{TIV}_t + \gamma' X_t + \epsilon_{t+4},$$

where $\Delta \mathrm{I}_{t+4}$ is one-year ahead changes in investment, TIV_t interest rate uncertainty, and X_t is a vector of controls which includes the term spread, Federal funds rate, the Gilchrist and Zakrajšek credit spread, Moody's Baa-Aaa credit spread, VIX, and GDP growth.[7] Table 1 summarizes the results.

[Insert Figure 2a and Table 1 here.]

[7] As a right-hand side variable, we also include lagged values of changes in investments, where we determine the optimal lag length using the Bayesian Information criterion.

Corroborating our earlier observation, we find the estimated coefficient on interest rate uncertainty, $\hat{\beta}$, to be negative and highly statistically significant (t-statistic of -4.35). The coefficient is not only statistically significant but also economically meaningful. For example, for any one standard deviation change in interest rate uncertainty, there is on average a 0.435 standard deviation change in the growth rate of aggregate investment which translates to an average \$52 billion movement.

In columns 2, 3, and 4, we add other predictors known to affect investment. Except for GDP growth and the term spread, we find none of the other variables to have significant predictive power for aggregate investment. Interest rate uncertainty, on the other hand, is statistically significant in all specifications and carries a negative sign. Also note that TIV remains negative and significant even after inclusion of other variables likely proxying for uncertainty, such as the VIX, indicating that interest rate uncertainty affects economic activity beyond financial market uncertainty. Equally interesting is the observation that interest rate uncertainty is also significant when including measures of financial distress, such as the aggregate credit spread. In contrast, Gilchrist, Sim, and Zakrajšek (2014) find that the effect of firm level idiosyncratic uncertainty on firm level investments disappears once conditioning on credit spreads.

In columns 5 and 6, we use the residuals from regressing TIV onto the policy uncertainty index to see how much interest rate uncertainty matters beyond more general policy uncertainty. For example, Gulen and Ion (2015) find a negative effect of policy uncertainty on investment. We note that both qualitatively and quantitatively the results do not change: The coefficient on the residual is negative and highly statistically significant with t-statistics of -4.31 and -2.72.

In a similar spirit, we use residuals from regressing TIV onto the financial uncertainty index proposed in Jurado, Ludvigson, and Ng (2015) to gauge whether the effects of interest rate uncertainty are a mere reflection of overall financial market conditions, or whether TIV (and related measures) provide additional information. Columns 7 and 8 report the results. Even when conditioning on the overall financial uncertainty index, the effects of TIV remain strongly significantly negative.

In Table 2, we test the robustness of these results using three other proxies of interest rate uncertainty. We find the results to be qualitatively and quantitatively the same: The estimated coefficients for the uncertainty proxies are negative and significant for most of the specifications. Moreover, we also find that interest rate uncertainty has predictive power for other macro quantities such as real GDP and civilian unemployment.[8]

[Insert Table 2 here.]

These results suggest that interest rate uncertainty is associated with a significant slowdown in aggregate real activity, controlling for the standard predictive variables. Several explanations are potentially consistent with these observations. On the one hand, the real options literature has long emphasized that elevated uncertainty can lead corporations to delay investment projects when these are partially irreversible. While this channel is relevant for all forms of uncertainty, this discount rate effect certainly may also apply more narrowly to the interest rate related uncertainty which is the focus of our attention. On the other hand, more specifically, uncertainty about interest rate payments associated with debt financed investment expenditures may also inhibit exercising growth options - a cash flow effect. In the following, we provide suggestive evidence that the cash flow channel is likely important in the context of our results. While TIV driving out VIX as a predictor provides preliminary evidence to that effect, we further examine the empirical links between interest rate uncertainty at the firm level.

2.2.2 Firm level results

While we find the empirical linkages between TIV and aggregate economic activity instructive, they ultimately need to originate in firms' response to interest rate uncertainty. Using panel regressions, we now document a number of stylized facts regarding the relationship between TIV and corporate policies at the firm level. Dissecting our evidence at the firm level is important, as it allows to better control for investment opportunities, but also, by exploring cross-sectional heterogeneity, we gain further insights regarding the potential mechanisms underlying our results.

Table 3 reports predictive regressions from one-year ahead firm level investment on TIV and other firm level controls, among which importantly, we add Tobin's Q, a common proxy

[8] These results are reported in the online appendix. Again, the results remain qualitatively and quantitatively unchanged when we use one of the three proxies of interest rate uncertainty instead of TIV.

of firms' investment opportunities. Including such a measure is crucial in order to alleviate concerns that declines in investments are driven by declines in investment opportunities. In line with the aggregate results, we find that higher interest rate uncertainty lowers firm level investment. The coefficient is highly statistically significant (t-statistic of -9.52) even when we control for a host of other variables. This result is of great significance 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 seem to assign an important role to financing constraints and financing in the transmission from interest rate uncertainty to corporate policies. The other columns in Table 3 explore this link further. We report regressions of predictive regressions of investment on TIV and TIV interacted with a host of other constraint measures.

[Insert Table 3 here.]

To measure to what extent a firm is financially constrained we use the Altman (1968) Z-score, Whited and Wu (2006), Hadlock and Pierce (2010), and Kaplan and Zingales (1997) indices, and firm size. 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, HP index, and KZ index) financially constrained firms cut future investment more heavily compared to unconstrained firms. Moreover, we find that the estimated coefficient on TIV remains significant and has a negative sign.

This finding provides further evidence that a cash flow mechanism is at work shaping the negative link between TIV and corporate investment. Table 4 provides additional evidence from a related angle. If uncertainty about future interest payments affects firms' investment decisions in periods of elevated interest rate uncertainty, we would expect the effect to be stronger in more highly levered firms. On the other hand, we would expect it to be immaterial for firms without leverage. As a matter of fact, a negative link between TIV and investment in unlevered firms would be more likely ascribed to the standard real options channel.

[Insert Table 4 here.]

The second column in Table 4 confirms that the effect in more highly levered firms is indeed stronger, as can be seen from the significant interaction term with book leverage. We next consider, going beyond our sample of firms, a sample of unlevered companies, sometimes referred to as zero leverage firms (see e.g., Strebulaev and Yang (2013)). Consistent with the previous result, we see that the effect in that sample is substantially weakened, as a matter of fact, the point estimate is no longer statistically significantly different from zero (t-statistic of -1.32). This suggests, in line with our intuition, that the cash flow effect is not at work in these firms, and equally importantly, there is no evidence that the real options effect is either.

The latter results pointing towards a cash flow mechanism are important, as uncertainty about future interest payments can be hedged through the swap market. Hence, it is natural to ask whether and how firms hedge their interest rate exposure? To provide answers to that question, we next examine evidence regarding corporate interest rate risk management practices.

2.3 Determinants of interest rate risk management

We first report and describe simple summary statistics regarding swap usage in our sample and then provide a more detailed cross-sectional analysis of interest rate risk management practices. Thereafter, we ask how risk management policies affect corporate investment policies.

2.3.1 Interest rate risk management summary statistics

In our data sample, 63% of all firms use swaps. Panel A of Table 5 reports summary statistics of interest rate swap usage and floating rate debt for our sample. For the average firm-year, 37.4% of the outstanding debt has a floating interest rate exposure. The average swap is equivalent to 6.9% of the firm's debt, but since some firms swap to floating while others swap to fixed, a net average of 1.7% of the firm-year's debt is swapped to a floating interest rate exposure, leaving the average firm-year with 35.7% of floating rate debt.

[Insert Table 5 here.]

These numbers echo the findings in Li and Mao (2003) and Chernenko and Faulkender (2011) who document that firms tend to be fixed rate payers. To further investigate swap usage in the cross-section of firms, we divide our sample into small and large firms, where small (large) firms are those below (above) the median firm size, as a first pass. Firm size is a natural variable to look at, as it is captures firms' evolution over the life cycle. Following the theoretical insights of Froot, Scharfstein, and Stein (1993), more constrained firms are more likely to engage in risk management activities. Hence, smaller firms should make more use of derivatives. Stulz (1996) finds, however, that large companies make far greater use of derivatives 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 46.4% of their initial debt with floating rate exposure, while large firms only have 31.3%. Hence, the net average which is swapped to a fixed interest rate exposure is 4.8% for small firms, but large firms swap to a floating rate exposure which is 0.8% 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 6.7% of their outstanding debt, whereas large firms swap 7% thereof.

In Figure 2b we plot the absolute value of percentage swapped to floating for small and large firms over the years 1994 to 2014. Two observations are noteworthy. First, small firms consistently hedge more than large firms. Especially between 2005 and 2014, 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 decreased again with the exception of the 2008 financial crisis when hedging of small firms increased. For small firms, hedging activity increased by more than one third during 2008-2009.

[Insert Figures 2b here.]

To gauge in more detail the difference between swap and non-users, Table 6 reports firm characteristic for swap and non-swap users. Swap users tend to be smaller firms, have a lower leverage ratio, a higher Tobin's Q, more cash, lower investments, are less profitable and have a higher cash flow volatility. Also note that firm characteristics are highly statistically different between swap users and non users.

[Insert Table 6 here.]

2.3.2 Interest rate risk management in the cross-section

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).[9] Panel A sorts % amount swapped, Panel B sorts the |% swapped|, and Panel C sorts total hedging. The results are reported in Table 7. In line with the results in Table 5, we note from Panel A, first column, that small firms are fixed rate payers and swap on average 8.1% of their outstanding debt. Large firms are floating rate payers and swap on average 2.7% of their initial exposure. The sorts also reveal that firms with less long-term debt and less cash tend to swap more (both in percentage and in absolute terms) and similarly, firms with a lower Tobin's Q are more prone to engage in swap usage.

[Insert Table 7 here.]

In absolute terms, we find that firms in the upper tercile of cash, swap 9.53% whereas firms in the lower tercile swap 8.97%. The difference is 0.55% and statistically different from zero. Similarly, firms in the lower tercile of Tobin's Q distribution, swap 8.26% whereas firms in the upper tercile swap 10.47%. The difference (2.2%) is again highly statistically different from zero. The same picture emerges from the total hedging variable which includes cash holdings. Small firms hedge 11.7% while large firms hedge 8.5%, the difference is 3.2% 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.

2.3.3 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

[9] Note that we only use the sample of swap users.

firm. This therefore suggests that we should expect constrained firms to benefit more from hedging and are therefore more likely to engage 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 Farre-Mensa and Ljungqvist (2015) for a recent discussion), we rely on two common ones that we choose for their simplicity and widespread use: In Panel B of Table 8 we make use of the Whited and Wu (2006) index, while Panel C reports double-sorts using the Hadlock and Pierce (2010) index. 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 the simplest measure of financial distress, corporate credit spreads.[10]

[Insert Table 8 here.]

Table 8 reports the main results by means of sorts. Panel A 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 show double sorts on constraint measures and credit spreads. The results confirm the evidence from the univariate analysis. More financially constrained firms hedge more, even after controlling for their distress risk, while more distressed firms hedge less, even after controlling for their financing constraints.

[10] The online appendix shows results using firms' expected default frequency and we find them to be quantitatively the same as for credit spreads.

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.

2.4 Interest rate uncertainty, risk management, and corporate policies

So far, we documented substantial cross-sectional differences in swap usage. A natural question is to what extent interest rate risk exposure and risk management moves with interest rate uncertainty, as proxied by TIV. All else equal, one would expect that corporations would attempt to reduce exposure in times of high interest rate risk. Figures 3a and 3b provide some preliminary evidence to that effect.

Figure 3a depicts 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.

[Insert Figures 3a and 3b here.]

The previous pattern suggests that firms' swap usage also moves with TIV. Figure 3b illustrates that notion as we observe 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.

More formally, Table 9 reports predictive panel regressions on firm level variables such as next year's cash, |% swapped|, hedging, and debt composition.[11] In addition to TIV, we also include a battery of firm level controls.

[Insert Table 9 here.]

All corporate hedging variables such as cash, |% swapped|, hedging, and the percentage floating rate debt after inclusion of swaps are significantly affected by interest rate uncertainty. In particular, an increase in interest rate uncertainty leads to a highly significant increase in cash. For example, a one percent increase in TIV leads to a two percent increase in cash holdings which corresponds to $9.6 million for the average firm.[12] This is consistent with the intuition that in response to elevated interest rate uncertainty, firms become more cautious and engage more in hedging.

2.5 Interest rate risk management and firm level investment

If a cash flow channel is underlying the negative relationship between TIV and investment, the possibility of hedging interest rate uncertainty should affect that link. In Table 10, we report results to that effect. Panel A documents that risk management significantly attenuates the adverse effects of interest rate uncertainty on investment in financially constrained firms. The interaction term of TIV with any of the hedging variables is positive and significant. Accordingly, the impact of interest rate uncertainty on corporate investment significantly depends on hedging activity and liquidity positions for constrained firms. On the other hand, it is quite revealing that all these effects are indistinguishable from zero in financially unconstrained firms, as documented in Panel B where we find none of the interaction terms to be statistically significant.

[Insert Table 10 here.]

[11] All t-statistics are calculated using robust asymptotic standard errors which are clustered at the firm level.

[12] In the online appendix we document that a firm's profitability and R&D spending are also negatively affected by interest rate uncertainty.

3 Model

Motivated by the stylized evidence documented in the previous section, we now develop a dynamic model of corporate investment and interest rate risk management. Apart from providing a quantitative rationale for our empirical findings, the model helps us to gauge the magnitudes of the real implications of movements in interest rate uncertainty. Although we view our empirical estimates as revealing, they do not formally extend far beyond suggestive correlations in the absence of a valid instrument. Under the assumptions and restrictions of the model, we can identify these effects quantitatively. We view this as informative, as the model is tightly calibrated to the corporate policies and risk management practices observed in our data set.

A realistic representation of firms' interest rate risk exposure requires both an accurate account of aggregate interest rate dynamics and corporations' debt structure. The model therefore consists of two building blocks. The first is a representation of the dynamics and the pricing of the aggregate interest rate environment. Apart from stochastic short-term interest rates, we allow for stochastic volatility as a tractable way to capture uncertainty about the future path of interest rates. By directly parameterizing a stochastic discount factor that specifies the pricing of interest rate risks, we obtain a flexible affine term structure model. The second building block is a model of a cross-section of firms, which, given the stochastic discount factor and aggregate interest rate 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, costly equity issuance and, given a preferential tax treatment of debt, using leverage. Regarding debt structure, we assume that there are two types of debt contracts 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 payments, 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.

3.1 Setup

We model a cross-section of firms i 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.

Interest Rate Risk and Uncertainty We distinguish between interest rate risk, namely stochastic changes in the risk-free short-term interest rate, r_t, and interest rate uncertainty, that is, stochastic movements in its conditional volatility σ_{rt}. The interest rate follows a mean-reverting process with stochastic volatility

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

with $\eta_t \sim \mathcal{N}(0,1)$, persistence $0 < \rho_r < 1$, and conditional volatility σ_{rt}. The conditional variance σ_{rt}^2 follows the process[13]

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

where $w_t \sim \mathcal{N}(0,1)$ and independent from η_t. Occasionally, we will refer to overall interest rate risks, meaning both interest rate risk and uncertainty.

Following Backus, Foresi, and Telmer (2001), we directly specify the stochastic discount factor that governs the pricing of aggregate interest rate risks. The stochastic discount factor is given by

$$\log M_{t+1} = -r_t - \left(\frac{1}{2}\lambda_r^2 + \frac{1}{2}\lambda_\sigma^2\sigma_w^2\right)\sigma_{rt}^2 - \lambda_r\sigma_{rt}\eta_{t+1} - \lambda_\sigma\sigma_{rt}\sigma_w w_{t+1}, \tag{3}$$

where λ_r is the price of interest rate risk and λ_σ is the price of interest rate uncertainty. The process for the stochastic discount factor incorporates a number of relevant features. First, there is discount rate risk through stochastic interest rates. Second, by no arbitrage, we obtain a flexible, two-factor affine term structure model.

Firm Investment and Financing Apart from aggregate interest rate risks, a firm i also faces firm-specific profitability shocks, denoted z_{it}. We assume that firm i's profitability shock z_{it} follows the mean-reverting process

$$z_{it+1} = \rho_z z_{it} + \sigma_z \xi_{it+1}. \tag{4}$$

The assumption that z_{it} is firm-specific requires that $E[\xi_{it}\xi_{jt}] = 0$, 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

[13] Our specification clearly allows for negative conditional variances. In our quantitative work, we carefully select the calibration so that this does not occur in simulated samples

distribution of z_{it}. Given that signal, they make an entry decision, and upon entry, purchase a capital stock k_{it}. 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 π_{it} given by

$$\pi_{it} = (1 - \tau)(\exp(z_{it})k_{it}^{\alpha} - f), \tag{5}$$

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.

Firms are allowed to scale operations by adjusting the level of productive capacity k_{it}. This can be accomplished through intermittent investment, i_{it}, which is linked to productive capacity by the standard capital accumulation equation

$$k_{it+1} = (1 - \delta)k_{it} + i_{it}, \tag{6}$$

where $\delta > 0$ denotes the depreciation rate of capital. In our baseline case, we accommodate the real options channel by assuming that investment is irreversible, that is,

$$i_{it} \geq 0. \tag{7}$$

Dropping this constraint easily allows to accommodate fully reversible investment, in which the classical real options channel vanishes.

In line with the U.S. 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.

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_{it} and by hoarding liquid assets in form of cash, c_{it}. While debt comes with a tax-advantage, it is defaultable and thus requires a time-varying premium δ_{it} over the risk-free rate, so that the net interest rate that firms pay is given by $r_t+\delta_{it}$. We determine the premium endogenously below. On the other hand, hoarding cash comes with a holding cost of ζ. To retain computational tractability, we allow b_{it} to take negative values, in which case we interpret it as cash holdings. In other words, we rely on the common simplifying assumption that $c_{it} = -b_{it}\mathbb{I}_{\{b_{it}<0\}}$, that is, that cash is negative short-term debt, which precludes corporations from holding short-term debt and cash simultaneously. More precisely, we can then define cash holding costs as $\zeta(b_{it}) = \zeta b_{it}\mathbb{I}_{\{b_{it}<0\}}$.

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 stochastic discount factor. And third, there is *profitability risk* induced by the potential comovement between interest rates and profitability, so that interest rates and thus the costs of debt finance are high precisely when firms have profitable investment opportunities . 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. We view one-period swaps as a tractable representation of firms' net position across their swap portfolios, which realistically they can adjust every period.

More specifically, we assume banks 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. Other than fixed costs, swaps do not consume resources ex ante, but either free up or consume resources ex post, depending on the short rate realization. We denote the notional amount of swap contracts purchased at time t by s_{it}. Whenever $s_{it} > 0$, the firm is a net floating rate payer, while $s_{it} < 0$ 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

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

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. This is in line with Bolton and Oehmke (2015), who discuss 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' equity payout, denoted by e_{it}. Equity payout and financing decisions must satisfy the following budget constraint

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

The budget constraint recognizes the tax deductibility of the coupon payments on long-term debt and on floating rate short term debt, as well as 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

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

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

$$d_{it} = e_{it} - \lambda(e_{it}). \tag{11}$$

Valuation The equity value of the firm, V_{it}, 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_{it} reaches zero. We 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 investment, i_{it}, short-term debt, b_{it}, and swap positions s_{it} to maximize the equity value of each firm. Note that the assumption that short-term debt can take negative values, conveniently accommodates cash holdings. The equity value can then be computed as the solution to the dynamic program

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

where the expectation on the right-hand side is taken by integrating over the joint conditional distributions of 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

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

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 values into short-term debt recovery

R_{it}^s and long-term debt recovery R_{it}^l. Under these assumptions, the payments on short-term debt must satisfy the Euler condition

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

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

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

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 χ_{it} in an iid fashion from a uniform distribution defined on the support $[0, X]$. At the same time, they draw a signal about next period realization of their idiosyncratic profitability shock z_{it+1}. Conditional on that signal, firms enter whenever their maximum expected firm value exceeds the entry cost, that is, whenever

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

The entry condition 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 their conditional volatility, as well as firm level conditions, namely the signal about future firm productivity.

Discussion The previous paragraphs introduced a dynamic model of corporate investment and interest rate risk management in the presence of interest rate uncertainty and financial frictions. The possibility of default and the associated deadweight costs of restructuring and liquidation, as well as equity issuance costs, give scope to value-enhancing hedging of aggregate interest rate risk and uncertainty 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. Lower interest rates and lower uncertainty 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. 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 can 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 and thus foster investment, which tends to push 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. Both larger and smaller firms with valuable growth opportunities benefit from the latter. Whether or not some firms are net floating rate payers thus depends which of these channels dominates, which is a quantitative question. In any case, by the preceding arguments, we intuitively expect the aggregate swap position in the economy to be related to the firm size distribution.

Swaps can also be used to partially hedge interest rate uncertainty. A similar intuition as above applies and is reinforced with interest rate uncertainty. Firms whose liquidity needs are concentrated in high interest rate states will find it more beneficial to be net fixed rate payers during high conditional volatility states, as the ex post gains from paying the fixed rate versus the floating rate are higher. Similarly, firms whose liquidity needs are concentrated in low interest rate states will benefit more from being net floating rate payers ex post in high uncertainty times.

In the next section, we examine the model mechanisms quantitatively by means of calibrations. We calibrate the model tightly to the corporate policies documented in our data set. Quantitatively, our model thus replicates the empirical finding that larger firms are net floating rate payers while smaller firms are net fixed rate payers, so that the financing channel dominates for the latter. With such a quantitative laboratory at hand, we can gauge the quantitative effects of interest rate uncertainty on real activity and, through the lens of the model, investigate the mechanisms underlying our empirical findings in more detail by means of counterfactuals.

3.2 Calibration

The model is calibrated at an annual frequency. We summarize our parameter choices in Table 11, panel A. Our benchmark model requires that we specify 16 parameters belonging to three groups: five for financing costs, six for technology, and five 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 short rate dynamics, investment rates, corporate credit spreads, 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.

[Insert Table 11 here.]

For the purpose of our annual calibration, we identify the short rate with the one-year U.S. Treasury rate, and choose the short rate parameters to match its mean and its autocorrelation. Similarly, our calibration matches the movements in the conditional volatility of one-year U.S. Treasury rates. Our calibration strategy for the risk price parameters is linked to empirical targets in the Treasury and in the corporate bond market. In particular, we choose λ_r to generate a realistic ten-year term spread on U.S. treasuries. The positive term spread requires λ_r to be negative. On the other hand, it is well known that λ_σ is difficult to pin down empirically (see e.g., Bikbov and Chernov (2009) and Collin-Dufresne, Goldstein, and Jones (2009)). We start from the assumption that high volatility episodes are bad times for investors, so that λ_σ is negative, and choose it to generate realistic average levels of the ten-year credit spread in our sample. The notion that risk pricing parameters in bond markets can be linked to credit spreads is referred to as "credit spread puzzle" and is studied in e.g. Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010), and Bhamra, Kuehn, and Strebulaev (2010). Since default costs represent one rationale for risk management in our model, matching credit spread dynamics appears relevant.

Our calibration of the technological parameters (ρ_z, σ_z, α, f, δ, and τ) follows the literature. We set the capital share α of production equal to 0.65 and 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).

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. We start by setting the issuance cost parameters in equity markets to match the size and frequency of new issuances. These choices also help us match realistic leverage ratios and cash holdings. In general, our parameter choices are consistent with the estimation results in Gomes (2001), and Hennessy and Whited (2005, 2007). 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. 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.

We solve the model using discrete state space dynamic programming methods. A description of the computational procedure can be found in the online appendix. 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 1,600 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 50 times. We proceed analogously when running regressions on simulated data.

3.3 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 11, Panel B, 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, investment, and hedging policies, and aggregate moments related to interest rates on government and corporate bonds.

Regarding corporate investment and financing policies, the results illustrate that the calibrated model is generally consistent with the data. Specifically, it shows cross-simulation averages of investment rates, the average market leverage and its cross-sectional dispersion, the frequency and size of new equity issuances, average market-to-book ratio, profitability, and cash holdings.

In order to generate realistic interest rate risk exposure and 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 be 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 averages. 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.

The model is consistent with properties of the short-rate, taken to be the one-year Treasury rate, and the term spread on long term government debt. The pricing of corporate short- and long-term debt is reflected in the one- and ten-year credit spreads. The model replicates these quite well. This is because the stochastic discount factor incorporates significant premia for movements in both short term interest rates, as well as their conditional volatility. Given negative prices of risk, investors dislike episodes of elevated interest rates and volatility, in which firms are more also more likely to default. Credit spreads thus contain substantial default risk premia, as in Chen, Collin-Dufresne, and Goldstein (2009), Chen (2010), Bahmra, Kuehn, and Strebulaev (2010, 2011).

Finally, the model is consistent with basic facts about corporate swap usage. First of all, as in the data, a significant fraction of firms does not use swaps at all. Within the context of the model, this is rationalized by an appropriate choice of the fixed cost of entering into a swap contract, ψ. Moreover, given realistic interest rate risk exposure and risk management incentives, the model also replicates the overall amount and direction of swap usage. Specifically, firms are fixed rate payers on average, as in the data.

The direction of swap usage depends on firm characteristics and the average direction therefore on the cross-sectional distribution of firms. Table 12 (Panel B) illustrates the distribution in the model averages of unconditional correlations between firm characteristics together with their empirical counterparts (Panel A).

[Insert Table 12 here.]

While perhaps not surprisingly slightly high, the correlations are generally qualitatively in line with the data. 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 debt portfolio. Because short-term debt comes in form of a one-period floating rate bond, the model rationalizes the empirical patterns on the fixed versus 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. 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 fixed costs.

Firm characteristics and their cross-sectional distribution also shape corporate risk management practices. Table 13 illustrates cross-sectional risk management implications by reporting unconditional univariate sorts of percentage of debt swapped along various firm characteristics. These sorts illustrate both the swap direction as well as the overall position.

[Insert Table 13 here.]

Qualitatively, the model replicates the empirical evidence well. 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. 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, they 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. As a consequence, they exhibit less volatile cash flows, thus hedge less on average, and benefit from transferring resources to low interest rate states, so they end up being floating rate payers. In the model, firms with high Tobin's Q and high credit spreads tend to use swaps more extensively, and are fixed rate payers on average, as they tend to be smaller.

3.4 Counterfactuals

In the previous section, we documented that the calibrated model captures basic properties of firms' investment, financing and risk management policies quantitatively well. We now use simulated data as a laboratory to further investigate the mechanisms underlying our empirical finding linking interest rate uncertainty and real activity, through the assumptions and restrictions of the model. We do so by reporting the results of panel regressions of one-year ahead firm level investment on interest rate uncertainty, and controls, in data simulated from various specifications nested in our benchmark model.

Table 14 reports the results. The first five entries document the empirical counterpart and then report a first set of results that are indicative of the main economic forces behind our empirical results. The empirical result uses realized variance of a one-year constant maturity Treasury yield as measure for interest rate uncertainty, which arguably corresponds most closely to the conditional interest rate variance σ_{rt}^2 in the model. The simulated regression results come from the following model specifications: (i) the benchmark model; (ii) a model with fully reversible investment, thus lacking a real options channel; (iii) a model in which firms are exclusively equity financed; and (iv) a model with equity financing only, and fully irreversible investment.

[Insert Table 14 here.]

First of all, we note that, perhaps unsurprisingly, the benchmark model captures the slowdown of future investment in high interest rate uncertainty episodes quantitatively well. The coefficient on interest rate volatility is negative, quite close to its empirical counterpart, and strongly significant. Perhaps more revealing is the observation that the corresponding coefficient remains significantly negative once we remove the irreversibility constraint on investment. The coefficient is slightly smaller now, but arguably only marginally so. This is informative as in this model specification the classic real options channel of waiting to invest in times of high uncertainty is not operative, so that any negative effect of interest rate uncertainty on investment (which we can causally identify given the assumptions and restrictions of the model) must work through alternative channels.

Specification (iii) retains investment irreversibility, but restricts firm financing to equity instruments only, so that the cash flow channel associated with uncertain debt payments is not at work here. The link between interest rate uncertainty is now substantially weakened. The relevant coefficient is still negative, although only marginally significant. This result is in line with our earlier interpretation that the real options channel likely is at work empirically, but that it does not quantitatively account for the bulk of the effect. Indeed, considering specification (iv) with both investment irreversibility and debt financing frictions removed, the effect disappears. The point estimate of the relevant coefficient is still slightly negative, but statistically very far from being significant.

Interpreting the data through the lens of our model thus confirms the intuition that much of the negative link between interest rate uncertainty and real activity works through a cash flow channel, rather than just a classic real options mechanism. This is noteworthy as one would expect that firms could hedge parts of the uncertainty about future interest rate payments. The next two entries in Table 14 provide some counterfactual experiments regarding risk management. In model specification (v) we remove firms' access to swaps as a risk management tool, while in (vi), we give firms access, in addition to simple interest rate swaps, to interest rate variance swaps, which allow them to exchange the realized variance of interest rates with the expected variance. Such an instrument, akin to interest rate swaps, allow firms to transfer resources from high to low variance states, and vice versa. In a world such as ours where interest rate variance is a distinct risk factor, firms might want to hedge adverse variance states separately. Notably, in stark contrast to interest rate swaps, firms in reality do not appear to make extensive usage of them as risk management tools. This is in spite the fact that these instruments, although apparently not widely traded, can be easily synthesized as an appropriate portfolio of swaptions.

Removing firms' ability to engage in interest rate risk management by means of swaps, amplifies the effects of interest rate uncertainty on real activity, and statistically significantly so. This is in line with the empirical results suggesting that the impact of uncertainty depends on firms' liquidity positions and hedging activity. Similarly, within the context of the model, interest rate variance swaps appear to be a valuable risk management instrument in that the negative effect of uncertainty is weakened. Interestingly, in spite of the presence of two distinct instruments to hedge the sources of interest rate risks, the effect does not disappear. Apart from real options effects, this is because hedging can be costly ex post, as it may consume resources depending on interest rate and variance realizations. Therefore, full hedging may not be optimal. On the other hand, from the model perspective, it raises the question why firms do not make extensive use interest variance swaps for hedging purposes.

The last two entries in table 14 report results from additional experiments that we find revealing. Reported are regression results from the following model specifications: in (vii) we simulate the benchmark model, but focus on sample paths without realized movements in the level of interest rates, the only aggregate shocks being innovations to the conditional volatility of the short-rate. In other words, there is interest rate uncertainty only, rather than interest rate risk. In (viii) we simulate the benchmark model, but as a sensitivity test we halve the volatility of the conditional variance of the short rate.

Inspection of case (vii) reveals that in spite of the lack movements in interest rates themselves, the economy exhibits significant fluctuations in real activity, namely investment. Moreover, movements in interest rate uncertainty are associated with a slowdown in future real activity which are quantitatively comparable to those in the data. While the real options channel is certainly at work here too, most of these fluctuations are driven by movements in the costs of debt financing: Elevated uncertainty about future interest rates raises default premia on short and long term debt in expectation and thereby makes financing investment by means of external finance more costly, leading to significant cuts in real activity. Specification (viii) suggests that the effects of interest rate uncertainty on real activity in the model are highly nonlinear, as even with small movements in interest rate uncertainty, the effects on investment are still substantial, and certainly not halved. While this is perhaps not too surprising in the context of a model exhibiting a host of fixed costs and thus nonlinearities, it suggests that even small movements in uncertainty can have significant real effects in a world with real and financial frictions.

Although the reported regression coefficients clearly fall short of a valid welfare criterion, within the context of our partial equilibrium model interest rate uncertainty emerges as quantitatively relevant obstacle to growth. While interest rate uncertainty also reflects market participants' responses to monetary policy and movements in bond markets unrelated to the latter, these findings suggest that policies of the Federal Reserve aimed at stabilizing expectations and reducing monetary policy uncertainty, such as various forms of forward guidance for example, may foster growth.

4 Conclusion

This paper documents novel empirical evidence that uncertainty about the future path of interest rates, labeled interest rate uncertainty, is associated with a significant slowdown of future economic activity. Our findings can be summarized as follows: First, interest rate uncertainty has adverse affects on investment both at the aggregate and firm level. Moreover, the effect is economically very large: For any one standard deviation change in interest rate uncertainty, there is a 0.4 standard deviation decrease in aggregate investments which corresponds to a more than $52 billion drop. Second, interest rate risk management significantly helps mitigate the adverse affects of interest rate risk uncertainty. Third, there are significant cross-sectional differences in swap usage according to asset and financing risk. To interpret our empirical findings, we then propose a tractable and parsimonious dynamic model which rationalizes and quantitatively matches the data.

Through the lens of the model, our empirical findings are consistent with an economic environment in which adverse movements in interest rate uncertainty are a source of slowdowns in economic activity. To the extent that interest rate uncertainty reflects uncertainty about the future stance of monetary policy, this finding has implications for the conduct of monetary policy. Specifically, it favors scenarios that reduce monetary policy uncertainty, such as uncertainty about the future path of the short-term interest rate as the Fed's main policy instrument, for example, by means of effective forward guidance. Clearly, our measures of interest rate uncertainty partially also reflect market participants' responses to monetary policy and disturbances in bond markets unrelated to the latter. Disentangling to what degree interest rate uncertainty and its real effects reflect monetary policy uncertainty will have important implications for monetary policy analysis and risk management practice. We leave this exciting and challenging topic for future research.

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5 Tables

Table 1
Predicting aggregate investment

This table shows predictive regressions from aggregate investment onto different variables. 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 criterion (BIC). The asymptotic t-statistics are reported in parentheses. In particular, for forecasting horizons $h \geq 1$, the MA(h) structure of the error term ϵ_{t+h} induced by overlapping observations is taken into account by computing standard errors according to Hodrick (1992). TIV refers to the Treasury implied volatility from Choi, Mueller, and Vedolin (2015). Aggregate investment is measured using real gross private domestic investment. Tiv - policy refers to the residuals from a linear regression of TIV on a constant term and the economic policy uncertainty index by Baker, Bloom, and Davis (2015). Tiv - financial refers to the residuals from an analogous regression on the financial uncertainty index by Jurado, Ludvigson, and Ng (2015). All regression coefficients are standardized to facilitate comparison among them. The sample period is from 1994 to 2014.

`Aggregate Investment: Forecast horizon 4 quarters`

model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
tiv	-0.435 (-4.35)		-0.267 (-2.09)	-0.368 (-2.44)				
tiv - policy					-0.448 (-4.31)	-0.405 (-2.72)		
tiv - financial							-0.279 (-3.11)	-0.222 (-2.23)
term spread	-0.800 (-4.64)	-0.615 (-3.36)	-0.802 (-3.28)	-0.733 (-3.14)	-0.881 (-5.21)	-0.815 (-3.37)	-0.577 (-3.09)	-0.507 (-2.56)
fed fund rate	0.226 (1.50)	0.237 (2.05)	0.333 (2.43)	0.139 (0.68)	0.397 (2.67)	0.294 (1.21)	0.155 (0.84)	0.005 (0.03)
gz spread		-0.330 (-2.12)	-0.206 (-0.93)					
baa - aaa				-0.142 (-1.05)		-0.149 (-0.98)		-0.277 (-3.87)
vix					-0.022 (-0.37)	0.021 (0.31)	0.072 (0.83)	0.128 (1.56)
gdp	0.465 (5.58)	0.529 (3.14)	0.473 (4.13)	0.446 (5.31)	0.474 (6.30)	0.450 (5.18)	0.531 (3.56)	0.477 (3.28)
Adj. R2	55.54%	58.75%	59.53%	55.58%	56.80%	56.83%	48.60%	50.60%

Table 2
Predicting aggregate investment

This table reports estimated coefficients for different proxies of interest rate uncertainty analogous to Table 1. Move stands for the Bank of America-Merrill Lynch Option Volatility Estimate (MOVE) index, RV1Y is the realized volatility on a one-year constant maturity Treasury yield and SPF3m represents the interquartile range of quarterly forecasts of the three-month Treasury Bill rate from the Survey of Professional Forecasters. Standard errors account for overlapping observations and are computed according to Hodrick (1992). As in Table 1, models (5) and (6) use the residuals from a linear regression of the corresponding interest rate uncertainty proxy on a constant term and the economic policy uncertainty index by Baker, Bloom, and Davis (2015). Columns (7) and (8) perform a similar analysis for the financial uncertainty index by Jurado, Ludvigson, and Ng (2015). The sample period runs from 1994 to 2014 and the asymptotic t-statistics reported in parentheses.

`Aggregate Investment: Forecast horizon 4 quarters`

model	(1)	(3)	(4)	(5)	(6)	(7)	(8)
move	-0.266	-0.180	-0.206	-0.225	-0.197	-0.157	-0.129
	(-6.90)	(-1.92)	(-2.44)	(-5.70)	(-2.93)	(-1.41)	(-0.91)
rv1y	-0.466	-0.330	-0.424	-0.451	-0.425	-0.373	-0.351
	(-2.75)	(-1.79)	(-2.19)	(-2.65)	(-2.27)	(-2.15)	(-1.91)
spf3m	-0.514	-0.402	-0.483	-0.481	-0.463	-0.487	-0.466
	(-3.14)	(-2.90)	(-2.95)	(-3.27)	(-3.04)	(-3.18)	(-2.92)

Table 3
Firm level investment: Financially constrained vs unconstrained firms

This table reports predictive panel regressions of next year's investment. All specifications also include a constant term and firm fixed effects (not reported). Standard errors are clustered at the industry level. The sample period runs from 1994 to 2014.

	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
tiv	-0.003	-9.52	-0.006	-4.16	-0.005	-4.74	-0.002	-2.89	-0.001	-1.83	-0.001	-1.89
tiv*size			0.001	2.75								
tiv*ww					-0.006	-2.67						
tiv*z							-0.000	-0.81				
tiv*hp									-0.001	-2.12		
tiv*kz											-0.001	-4.50
ww					0.065	3.42						
z							0.007	3.88				
hp									0.010	2.96		
kz											0.000	0.01
size	-0.023	-9.41	-0.024	-8.00	-0.022	-8.06	-0.020	-8.34	-0.017	-8.38	-0.024	-9.65
leverage	-0.191	-17.34	-0.193	-18.09	-0.231	-16.71	-0.189	-17.47	-0.193	-18.06	-0.180	-15.33
investment	0.095	4.45	0.090	4.31	0.068	2.93	0.087	4.48	0.093	4.45	0.094	4.43
long-term debt	0.004	1.27	0.007	2.03	0.007	1.74	0.008	2.24	0.006	1.68	0.004	1.11
Tobin's Q	0.004	2.60	0.003	1.85	0.003	2.11	0.003	2.22	0.003	2.25	0.004	2.44
Firm FE	Y		Y		Y		Y		Y		Y	
Industry Cluster	Y		Y		Y		Y		Y		Y	
Adj. R^2	3.88%		3.93%		2.46%		2.76%		4.12%		2.84%	
N	13,981		13,981		10,881		13,355		13,981		13,703	

Table 4
Firm level investment: zero leverage firms

This table reports predictive panel regressions of next year's investment. The sample of zero leverage firms includes all Compustat firms that have no debt outstanding during our entire sample period, available data for at least five consecutive years, and total assets larger than $5 million (total 349 firms). Zeroleverage is a dummy variable that equals 1 for a zero leverage firm and 0 otherwise. The last column shows regression results for the combined samples, i.e. our sample and all zero leverage firms. All specifications also include a constant and firm fixed effects (not reported). Standard errors are clustered at the industry level. The sample period runs from 1994 to 2014.

	Our Sample		Our Sample		Our Sample		Zero Leverage		Combined	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
tiv	-0.003	-9.52	-0.002	-5.81	-0.003	-11.93	-0.001	-1.32	-0.003	-12.13
tiv*bookleverage			-0.002	-1.97						
tiv*zeroleverage									0.002	3.37
size	-0.023	-9.41	-0.021	-8.99	-0.018	-6.89	0.004	1.30	-0.016	-5.93
leverage	-0.191	-17.34								
bookleverage			-0.071	-4.02						
investment	0.095	4.45	0.084	4.12	0.099	4.71	0.201	4.11	0.111	5.15
long-term debt	0.004	1.27	0.000	0.08						
Tobin's Q	0.004	2.60	0.009	3.41	0.003	2.34	0.004	3.05	0.003	2.69
Firm FE	Y		Y		Y		Y		Y	
Industry Cluster	Y		Y		Y		Y		Y	
Adj. R2	3.88%		3.90%		4.36%		6.23%		1.94%	
N	13,981		13,139		18,554		2,626		21,180	

Table 5
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. Swap users are firms that use interest rate swaps at least once during the sample period. Initial % floating is the 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 five years to maturity. The sample period runs from 1994 to 2014.

variable	N	mean	stdev	min	max
Panel A: All Companies					
initial % floating	17,631	37.423	31.484	0	100
% swapped	19,304	-1.685	17.123	-100	100
|% swapped|	19,304	6.877	15.771	0	100
% floating	17,631	36.218	29.466	0	100
long-term debt	17,389	40.038	31.948	0	100
Panel B: Small Companies					
initial % floating	7,163	46.382	35.794	0	100
% swapped	8,625	-4.842	18.090	-100	100
|% swapped|	8,625	6.698	17.488	0	100
% floating	7,163	41.989	33.605	0	100
long-term debt	7,759	30.028	34.725	0	100
Panel C: Large Companies					
initial % floating	10,468	31.292	26.466	0	100
% swapped	10,679	0.865	15.848	-100	100
|% swapped|	10,679	7.022	14.233	0	100
% floating	10,468	32.270	25.521	0	100
long-term debt	9,630	48.103	26.940	0	100

Table 6
Firm characteristics

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 2014.

	total	users	non users
log(sales)	7.386	6.748	7.710***
N	22,801	7,690	15,111
leverage	0.156	0.107	0.181***
N	22,198	7,563	14,635
initial % floating	0.374	0.356	0.380***
N	17,631	4,325	13,306
% floating	0.362	0.356	0.364
N	17,631	4,325	13,306
Tobin's Q	2.072	2.439	1.881***
N	22,365	7,633	14,732
size	7.501	6.844	7.836***
N	22,822	7,709	15,113
cash	0.097	0.144	0.073***
N	22,580	7,646	14,934
investment	0.090	0.083	0.094***
N	21,224	7,267	13,957
profitability	0.141	0.134	0.144***
N	22,785	7,689	15,096
CF volatility	0.102	0.123	0.091***
N	22,722	7,701	15,021

Table 7
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 |% swapped|(Panel B), and hedging (Panel C). 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. The data cover the period from 1994 to 2014.

	size	lt debt	cash	Tobin's Q
Panel A: % swapped				
low	-8.114	-8.416	-3.791	-3.158
mid	-1.721	0.460	-2.960	-1.834
high	2.671	1.462	0.319	-1.086
total	-2.211	-2.117	-2.221	-2.045
high - low	10.785***	9.878***	4.110***	2.072***
Panel B: |% swapped|				
low	10.545	12.101	8.977	8.269
mid	9.518	7.929	9.289	9.042
high	7.826	7.471	9.532	10.467
total	9.253	9.145	9.257	9.234
high - low	2.719***	4.630***	0.554*	2.198***
Panel C: total hedging				
low	11.717	11.699	4.457	8.501
mid	10.358	8.641	7.793	9.260
high	8.513	9.617	18.429	12.787
total	10.209	9.985	10.209	10.189
high - low	3.204***	2.083***	13.972***	4.286***

Table 8
Double sorts of |% swapped|

Panel A reports univariate sorts of |% swapped|along terciles of five-year credit spread, five-year expected probability of default (EPD), the WW index, and the HP index. The rest of the table reports unconditional double sorts of |% swapped|along the WW index and credit spread (Panel B) and the HP index and credit spread (Panel C). 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. The data cover the time period from 1994 to 2014.

Panel A: Univariate Sorts

	1	2	3	Total	Low - High
Credit Spread	9.945	8.493	8.002	8.818	1.942***
EPD	9.701	9.538	8.596	9.275	1.104***
WW index	9.168	9.484	10.551	9.718	1.383***
HP index	7.336	9.305	10.795	9.098	3.459***

Panel B: WW Index & Credit Spread

	Credit Spread				
WW-Index	Low	Mid	High	Total	Low - High
low	10.288	6.488	6.180	8.070	4.108***
mid	11.280	8.283	7.933	9.252	3.347**
high	11.441	8.460	8.228	9.487	3.213**
total	10.879	7.749	7.642	8.766	
low - high	1.153	1.972*	2.048*		

Panel C: HP Index & Credit Spread

	Credit Spread				
HP index	Low	Mid	High	Total	Low - High
low	9.181	8.062	4.834	7.812	4.347***
mid	10.997	8.995	8.493	9.305	2.504*
high	14.068	9.989	10.219	10.766	3.850**
total	9.963	8.616	7.636	8.743	
low - high	4.887***	1.927*	5.385***		

Table 9
Interest rate uncertainty and corporate hedging: panel regressions

This table reports predictive panel regressions on firm level variables such as next year's cash, |% swapped|, hedging and % floating. All specifications also include a constant term and firm fixed effects (not reported). Standard errors are clustered at the industry level. The sample runs from 1994 to 2014.

	cash_t+1		|% swapped_t+1|		hedging_t+1		floating_t+1	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
tiv	0.002	8.77	0.001	2.03	0.002	6.77	-0.004	-4.29
size	-0.008	-4.26	0.000	0.03	-0.008	-3.44	-0.008	-0.98
leverage	-0.012	-1.12	0.077	3.66	0.022	1.65	-0.109	-4.15
investment	-0.034	-4.45	0.083	3.64	-0.013	-1.20	0.021	0.64
long-term debt	-0.001	-0.34	-0.020	-3.05	-0.003	-1.16	-0.066	-6.33
Tobin's Q	-0.000	-0.12	-0.003	-1.36	-0.000	-0.07	-0.000	-0.12
log(GDP)	0.035	8.14	0.005	0.59	0.037	7.85	-0.056	-4.42
Lagged LHS	Y		Y		Y		Y	
Firm FE	Y		Y		Y		Y	
Industry Cluster	Y		Y		Y		Y	
Adj. R^2	60.55%		40.95%		51.46%		50.03%	
N	14,137		9,815		14,063		12,245	

Table 10
Corporate hedging and investment: constrained vs unconstrained firms

This table reports predictive panel regressions on next year's firm level investment. Panel A (panel B) reports the regression results for financially constrained (unconstrained) firms. A firm is considered financially constrained if the Whited and Wu (2006) index for that firm lies in the top tercile, otherwise a firm is considered financially unconstrained. All specifications also include a constant and firm fixed effects (not reported). Standard errors are clustered at the industry level. The sample period runs from 1994 to 2014.

Panel A: Financially Constrained Firms						
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
tiv	-0.004	-3.30	-0.005	-3.87	-0.005	-4.30
tiv*|% swapped|	0.006	2.22				
tiv*hedging			0.015	1.92		
tiv*cash					0.015	1.82
|% swapped|	-0.004	-0.94				
hedging			-0.059	-0.82		
cash					-0.051	-0.63
Controls	Y		Y		Y	
Firm FE	Y		Y		Y	
Industry Cluster	Y		Y		Y	
Adj. R2	5.23%		2.37%		2.03%	
N	1,910		3,291		3,301	

Panel B: Financially Unconstrained Firms						
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
tiv	-0.002	-5.33	-0.002	-6.39	-0.002	-6.48
tiv*|% swapped|	-0.002	-0.70				
tiv*hedging			-0.001	-0.45		
tiv*cash					-0.003	-0.81
|% swapped|	-0.005	-0.28				
hedging			0.053	2.04		
cash					0.132	3.70
Controls	Y		Y		Y	
Firm FE	Y		Y		Y	
Industry Cluster	Y		Y		Y	
Adj. R2	5.65%		4.03%		3.72%	
N	7,759		10,468		10,514	

Table 11
Calibration

This table summarizes the calibration used to solve and simulate our model (Panel A) and the unconditional moments of corporate policies and interest rates generated by the model (Panel B). All quantities are annual.

Panel A: Calibration		
Description	*Parameter*	*Value*
Cash holding costs	ζ	0.006
Interest rate persistence	ρ_r	0.86
Interest rate volatility persistence	ρ_σ	0.41
Interest rate volatility vol	σ_w	0.0002
Price of interest rate risk	λ_r	-3.12
Price of interest volatility risk	λ_σ	-2.36
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
Swap issuance costs	ψ	0.002
Depreciation rate	δ	0.12

Panel B: Moments		
Moment	*Data*	*Model*
Average investment rate	0.15	0.13
Average market leverage	0.28	0.34
Dispersion in market leverage	0.41	0.36
Frequency of equity issuances	0.07	0.06
Average new equity-to-asset ratio	0.12	0.10
Average market-to-book ratio	2.25	1.76
Average profitability	0.15	0.12
Dispersion in profitability	0.11	0.15
Average cash-to-asset ratio	0.09	0.08
Short-rate volatility	0.03	0.03
One-year credit spread	0.007	0.006
Ten-year credit spread	0.013	0.015
Ten-year term spread	1.02	0.57
Fraction of swap users	0.63	0.70
Absolute percentage swapped	0.068	0.076
Net percentage swapped	-0.016	-0.022

Table 12
Correlations

This table reports unconditional correlations between firm characteristics in the data (Panel A) and generated by the model (Panel B).

Panel A: Data					
size	1.00				
leverage	0.14	1.00			
long-term debt	0.31	0.25	1.00		
cash	-0.21	-0.28	-0.12	1.00	
Tobin's Q	-0.13	-0.39	-0.12	0.27	1.00
Panel B: Model					
size	1.00				
leverage	0.54	1.00			
long-term debt	0.67	0.59	1.00		
cash	-0.61	-0.52	-0.55	1.00	
Tobin's Q	-0.45	-0.48	-0.49	0.53	1.00

Table 13
Tercile sorts of swap usage: Model

This table reports univariate tercile sorts of % swapped along size, long-term debt, Tobin's Q, and credit spreads as a distress indicator from model simulations.

	size	long-term debt	Tobin's Q	credit spreads
Low	-0.122	-0.124	0.081	0.074
Mid	-0.024	-0.021	-0.027	-0.020
High	0.082	0.079	-0.119	-0.116

Table 14
Counterfactuals

This table reports the coefficients of panel regressions of next year's investment on interest rate uncertainty, and controls, in the data and in various model specifications. The empirical measure for interest rate uncertainty used here is realized variance on a one-year constant maturity Treasury yield, and its model counterpart is conditional variance σ^2_{rt}. The empirical sample period runs from 1994 to 2014, with a model counterpart of 20 periods. Model (i) is the benchmark model, ii) features fully reversible investment, iii) features equity financing only, iv) has fully reversible investment and equity financing only, v) has no swaps, vi) has both interest rate and interest rate variance swaps, vii) features shock series without realized interest rate level but interest rate variance variation, and viii) reduces the standard deviation of interest rate variance shocks by half. t-statistics are reported in parentheses.

	model							
data	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
-0.006	-0.011	-0.010	-0.006	-0.003	-0.013	-0.009	-0.007	-0.006
(-3.31)	(-2.91)	(-2.23)	(-1.82)	(- 0.95)	(-3.09)	(-2.68)	(-2.33)	(-2.42)

6 Figures

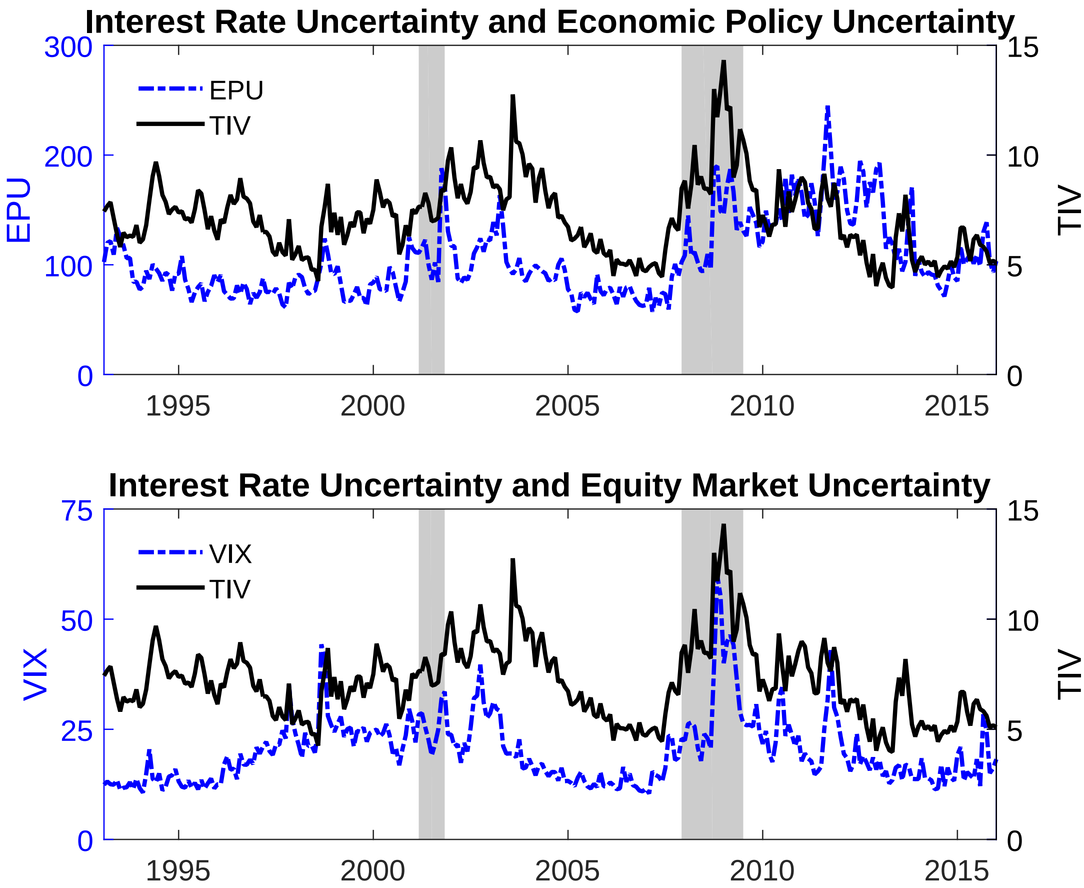
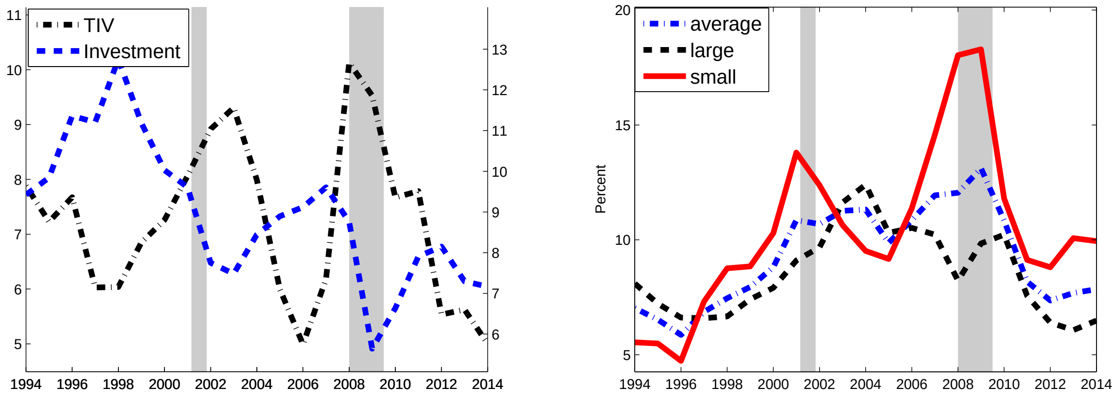


Figure 1. TIV and other proxies of uncertainty

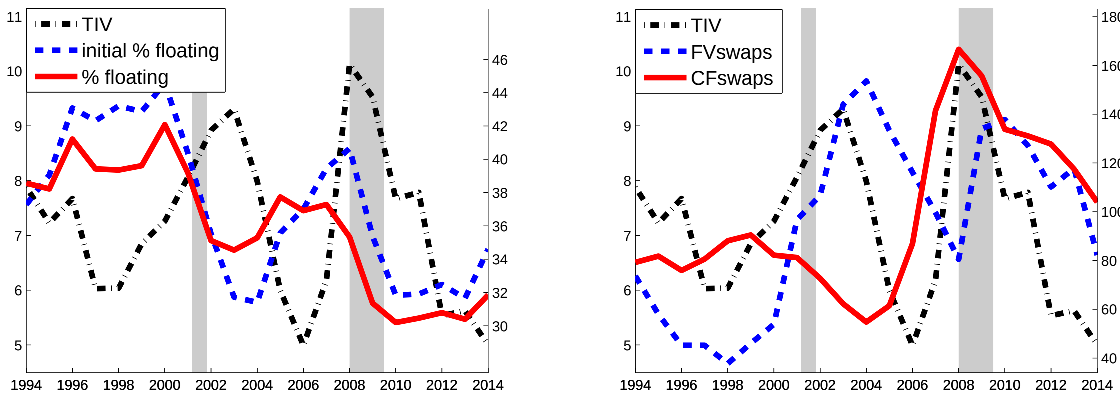
This figure plots a proxy of interest rate uncertainty (TIV) together with the economic policy index of Baker, Bloom, and Davis (2015) (upper panel) and with the VIX (lower panel). Data are monthly and run from 1994 to 2015. Grey bars indicate NBER recessions.



(a) TIV and investment

(b) Swap usage

Figure 2. The left figure plots Treasury implied volatility (TIV, left axis) and average investment (right axis). Investment for a specific firm is calculated as the sum of capital expenditure and acquisitions scaled by book assets. Average investment is the average of investment as a percentage of total assets across all our sample firms in a given year. Figure b) plots |% swapped|for the whole sample, large, and small firms. Grey bars indicate NBER recessions. Data are annual and run from 1994 to 2014.



(a) TIV and the fix-floating mix

(b) TIV and directional swap usage

Figure 3. Figure a) plots TIV (left axis), initial % floating, and % floating (both right axis). 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 b) plots the annual time series of TIV (left axis), average cash flow swap, and average fair value swap notionals (right axis). Reminder: A cash flow swap transforms floating into fixed rate debt, whereas a fair value swap does the opposite. Grey bars indicate NBER recessions. Data are annual and run from 1994 to 2014.