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July 2022

Assessing the Impacts of Uncertainty on Firm Performance

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This paper is submitted to McGill University in partial fulfillment of the requirements for the degree of Master of Arts in Economics.

Abstract

This paper empirically explores the extent to which economic uncertainty impacts firm performance. In particular, it uses a panel regression framework and structural vector autoregression approach to determine how uncertainty shocks affect firms' investment rates, total factor productivity growth, and risk of bankruptcy. Fixed effect panel regressions indicate that firm-level outcomes are negatively related with uncertainty and notably heterogenous across age. Structural analysis shows that, while not explaining a significant portion of variation in firm-level outcomes, uncertainty innovations lead firm performance measures to significantly deteriorate and rapidly rebound. On average, we show that a one standard deviation shock to uncertainty reduces firms' quarterly investment rates, productivity growth, and Altman Z-scores by around 0.10 percentage points, 1 percentage point, and 0.05 points, respectively. Cross-country comparisons reveal that firm activity in both Canada and the US is notably affected by cross-border economic policy uncertainty.

Keywords: Uncertainty, Firm Performance
JEL Code(s): C32, C33, D81

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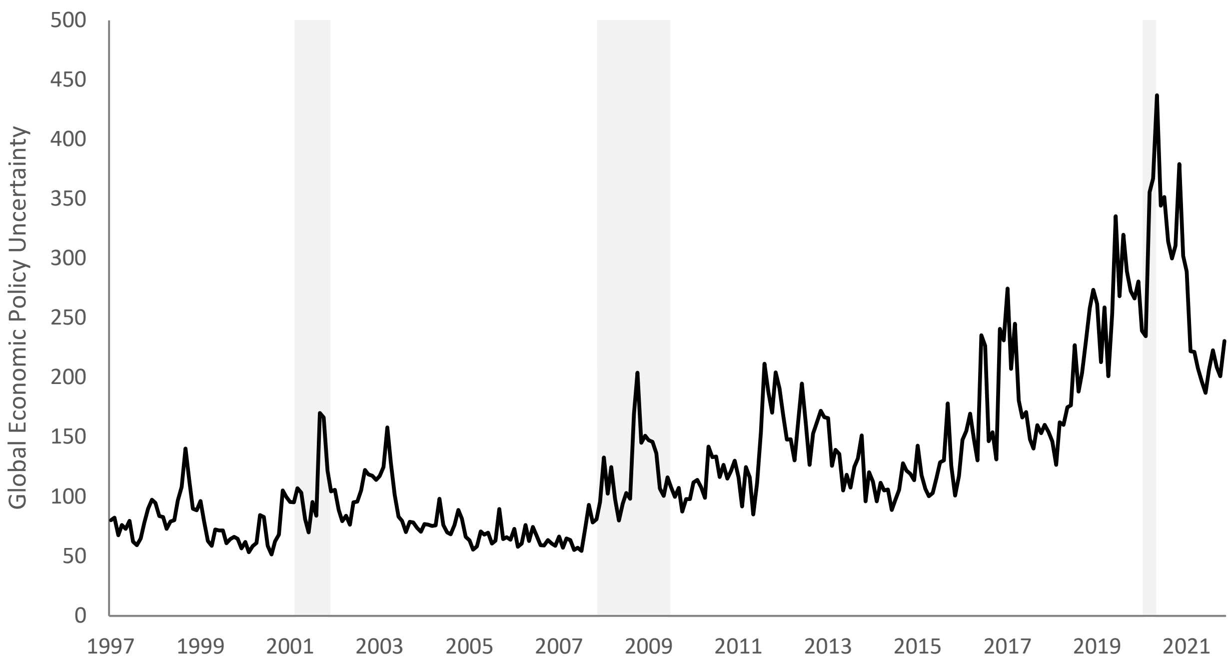
1. Introduction

Stability fosters economic growth by providing consumers, businesses, and institutions with a clearer outlook of the future (IMF, 2021). However, economic agents do not always have an unobscured forward-looking view. A sudden rise in the level of aggregate uncertainty can make it more difficult for households, firms, and financial intermediaries to confidently form expectations and accurately forecast the likelihood of future events (Bloom, 2014; Bernanke, 1983). In addition to having pronounced impacts on real economic activity, these uncertainty shocks have also been shown to play a key role in driving business cycle dynamics (Bloom et al., 2012; Bloom, 2014). It is for these reasons that uncertainty has become such an important area of research in modern macroeconomics, especially since the Global Financial Crisis of 2007-2008.

The degree of perceived uncertainty has been found to rise substantially in response to political developments, disasters, and conflicts. In the last 30 years, localized events such as the September 11th attacks, the Fukushima nuclear disaster, and the United Kingdom's referendum to leave the European Union have all been responsible for triggering a significant increase in global uncertainty (Ahir et al., 2018). In addition to rising abruptly as a result of unanticipated events, uncertainty is also known to be strongly countercyclical – meaning it consistently increases during recessions and falls during expansions (Bloom et al., 2012; Ludvigson et al., 2015). This occurs, in part, because worsening information asymmetries – which tend to accompany economic downturns – also spur uncertainty (Bloom, 2014).

Figure 1: Global Economic Policy Uncertainty



Note: The GEPU index comprises 21 countries which are weighted according to their national PPP-adjusted GDP. The index is normalized so its mean is equal to 100 between 1997 and 2015. Shaded regions denote US recessions, as defined by the National Bureau of Economic Research.
Source: Global Economic Policy Uncertainty (Baker et al., 2022)

Although there remains much debate around the extent to which uncertainty is a symptom or cause of recessions, it is undeniable that proxies for global uncertainty moved higher during the

Global Financial Crisis and have exhibited a notable upward trend in the years since (Bloom, 2014; **Figure 1**). Experts believe that rising uncertainty over this period was fueled predominantly by trade conflicts and geopolitical tensions (PwC, 2020). Policy uncertainty, which reflects risks arising from undefined or unstable government policies and regulations, has also been found to comprise an increasingly large portion of aggregate economic uncertainty (Fernandez-Villaverde et al., 2011). It is important to emphasize that rising uncertainty is not simply an innocuous stylized feature of the contemporary business environment, but rather a phenomenon with tangible consequences for leading decision-makers. In fact, in the 23rd edition of PwC's Annual Global CEO Survey, executives from around the world reported that uncertainty posed the single largest risk to their companies' growth prospects (PwC, 2020).

Global uncertainty reached new heights during the COVID-19 pandemic as risks surrounding the effectiveness of vaccines, the appearance and rapid spread of new variants, as well as the sporadic implementation of government-mandated restrictions made it more difficult for economic agents to adequately plan for the future (Baker et al., 2020b; Altig et al., 2020). In fact, throughout much of the pandemic, firms in Canada cited elevated uncertainty as a key driver of faltering forward-looking indicators (Bank of Canada, 2020). Like during the Global Financial Crisis, pandemic-era economic uncertainty was credited for making households and firms more cautious, and consequently more hesitant to consume or invest. This contributed to the exacerbation of already poor economic conditions – which were ultimately improved, in part, by extraordinarily accommodative monetary policy support and unprecedented fiscal stimulus in Canada and abroad (Bloom, 2014; IMF, 2022). The sheer magnitude of the COVID shock has arguably made research focused on uncertainty more relevant than ever before.

The impact of uncertainty on firms is of particular concern for policymakers because a high degree of perceived volatility can lead businesses to delay, reduce, or otherwise reconsider spending on hiring employees, increasing compensation, expanding capacity, or improving processes (Kupelian & Loughridge, 2017). In fact, as a result of its tendency to dissuade entrepreneurial risk-taking, past research has likened policy uncertainty, in particular, to a tax on investment (Rodrik, 1991). The propensity for business leaders to employ a so-called "wait and see" strategy during periods of high uncertainty is well documented and is responsible for slowing firms' response to changes in demand and overall business conditions (Bernanke, 1983; Bloom et al., 2007). Hesitancy to make investments in personnel, equipment, and business practices – even after uncertainty has subsided – has been shown to exacerbate downturns by deepening the initial decline in activity and prolonging the duration of the economic contraction (Council of Economic Advisors, 2004). This partly explains why predicting the speed of the global economic recovery during the COVID era was especially difficult (Boutilier, 2021).

Given what is known about the effects of uncertainty on economic activity, the primary goal of this paper is to assess to what extent uncertainty shocks affect firm performance. In particular, we empirically explore how, by how much, and for how long firms' investment rates, productivity growth, and risk of bankruptcy are affected by increases in uncertainty. In addition, we investigate heterogeneity in firm responses. That is, this paper determines whether the impact of uncertainty on firm outcomes varies meaningfully across firm size and age, whether Canadian and US-borne uncertainty elicit different firm responses, as well as whether a shock to aggregate uncertainty affects businesses in the same way as a rise in their own stock's return volatility.

This paper contributes to the existing literature in numerous ways. Firstly, although the mechanism through which uncertainty impacts economic activity is increasingly well understood in aggregate, micro-founded research focused on assessing firm-level impacts of uncertainty shocks – undertaken in this paper – remains comparatively limited. Secondly, this study assumes a wider empirical scope than much of the existing literature. Instead of using a single uncertainty measure in its analysis, this paper employs a selection of six proxies, encompassing both economy-wide and firm-level measures. In addition, this study explores the impacts of uncertainty on a number of prominent firm performance measures, instead of focusing on a single outcome variable of interest. Thirdly, this paper highlights the impacts of uncertainty on Canadian firms – which are less studied than their international counterparts. At the same time, it makes cross-country comparisons with the United States, which puts this paper's findings – as well as results from US-focused research – into greater context. In fact, to the best of our knowledge, this is the first paper to use Canadian firm microdata in its assessment of uncertainty shocks. Finally, this study offers insight into how firm-level economic activity was impacted by the COVID-19 pandemic. This event produced a unique and unprecedented uncertainty shock that has not yet been exhaustively examined in the literature due to its relative recentness, but undoubtedly remains of upmost interest to academics and policymakers alike.

Through the estimation of fixed effect regressions, this paper finds that uncertainty – whether proxied with aggregate or firm-specific measures – is associated with unambiguously lower firm-level investment rates. The impact of uncertainty on productivity growth and risk of bankruptcy, although generally negative, is found to be comparatively smaller in magnitude and less statistically significant. In addition, we show that the effects of uncertainty are dampened somewhat for more mature companies. Turning to the impulse response functions generated from the paper's structural vector autoregression (SVAR) models, we show that a one standard deviation shock to uncertainty immediately reduces firms' quarterly investment rates, productivity growth, and Altman Z-scores by around 0.10 percent, 1 percent, and 0.05 points, respectively. These firm performance measures rebound quite strongly and in some cases overshoot their long-run level in the quarters following the initial innovation – particularly when uncertainty is proxied by stock market volatility. Cross-country comparisons show that Canadian financial market and economic policy uncertainty have notable effects on US firm activity, and vice versa. In general, structural analysis points to a weaker relationship between uncertainty and firm-level economic activity than what is predicted by fixed effect panel regressions. This paper's findings are largely consistent with the literature and reiterate the importance of further micro-founded uncertainty-oriented research.

This rest of this paper is organized as follows. We begin by providing a thorough review of the relevant literature, focusing primarily on contributions made since the Great Recession. Next, we carefully present the empirical approach employed in the paper. This entails formally describing the firm-level financial data, uncertainty measures, and macroeconomic series used before subsequently outlining the panel regressions and vector autoregression framework employed to assess the firm-level impacts of uncertainty. We proceed to interpret regression results, as well as analyze variance decomposition and impulse response functions. Cross-country comparisons between Canada and the US are made throughout the paper. We conclude by discussing results, putting forward potential policy implications, and outlining avenues for future research.

2. Literature Review

The tendency for firms to behave more cautiously during periods of high uncertainty is often discussed through the lens of real options (Bernanke, 1983; McDonald & Siegel, 1986). This theoretical strand of the uncertainty literature postulates that firms choose to delay investment and hiring during periods of elevated uncertainty because the option value associated with waiting for business conditions to improve exceeds the value derived from executing risky decisions. Real option effects are found to be especially important when decisions are irreversible, when markets are imperfectly competitive, or when it is costly for firms to separate from their workers. Choosing to delay actions under these conditions may limits firms' ability to pursue profitable opportunities in the future (Bloom, 2014; Baker et al., 2016). Moreover, real option theory points out that – in addition to directly reducing investment and hiring in the short-run – uncertainty renders firms less sensitive to changes in business conditions (Bloom, 2000). That is, real options effects make firms slower to ramp up their activities, even as expectations of future growth improve. This phenomenon has implications for the effectiveness of countercyclical economic policies and helps explain why decreases in wages and prices – as well as expansionary monetary policy – may have limited impacts on firms' activities if the degree of perceived uncertainty is high (Fernandez-Villaverde et al., 2013; Baker et al., 2016).

Although the real options channel is the most frequently cited explanation for why uncertainty drives business cycle fluctuations, there are other mechanisms through which uncertainty is hypothesized to affect economic activity. As summarized by Baker et al. (2016), alternative channels include precautionary cutbacks in spending and increased financing costs. The former describes the process by which risk averse agents reduce their expenditure and build savings in order to better insulate themselves from uncertainty over future income. The latter reflects firms' tendency to deleverage in response to a tightening of financing conditions and widening of credit spreads during highly uncertain periods (Gilchrist et al., 2014). These are aptly referred to as "precautionary savings" and "financial friction" effects, respectively, by Jurado et al. (2015).

Existing literature concerned with empirically quantifying the causal effects of uncertainty on economic activity has predominantly sought to exploit natural sources of exogenous variation. The use of quasi-experimental techniques is necessary because the link between uncertainty and economic activity is endogenized by the countercyclicality of aggregate uncertainty.

Stein and Stone (2013) estimate the effects of uncertainty on various measures of US firm performance by leveraging exogenous variation stemming from macroeconomic fluctuations. Specifically, the authors exploit the fact that firms from different industries receive differential exposure to volatility in energy prices and currency markets. This variation is used to instrument for firm-specific volatility, which is itself proxied with realized stock return volatility and a forward-looking measure of uncertainty – namely, option-implied stock price volatility. The paper shows that firms exposed to more uncertainty tend to invest, hire, and advertise significantly less. In fact, the authors estimate that around half of the total decline in investment and hiring during the Global Financial Crisis can be attributed to uncertainty. At the same time, the paper finds that uncertainty propagates firms' spending on research and development projects. This result is consistent with more theoretical options literature which emphasizes the value of undertaking projects with long investment lags during periods of elevated uncertainty.

Research conducted by Baker et al. (2013) – and expanded by Baker et al. (2020a) – assesses the causal relationship between uncertainty and aggregate economic growth using data from 59 countries between 1970 and 2012. To do so, the paper instruments for uncertainty – which is itself proxied by stock market volatility – with a number of unanticipated events such as natural disasters, terrorist attacks, and political shocks including coups and revolutions. Through the paper's instrumental variable approach, both first and second moment shocks are shown to matter in explaining variation in GDP growth following a disaster. Second moment shocks are found to have around twice as large an impact as a similarly large first moment innovation, suggesting that uncertainty plays a crucial role in driving economic slowdowns. These results are consistent with findings put forward in Bloom et al. (2018), who use a dynamic stochastic general equilibrium framework to show that recessions are best modelled as being driven by shocks with a negative first moment and a positive second moment. On the other hand, Cesa-Bianchi et al. (2014) show that there exists a large and statistically significant relationship between future output growth and current volatility – but no meaningful effect of volatility shocks on business cycles. This suggests that volatility is a byproduct of economic instability, rather than a cause.

Other papers are less concerned with exploring the direction of the causal relationship between uncertainty and economic activity. Instead, they are interested in empirically exploring the magnitude of the link between uncertainty shocks and real economic activity.

For instance, Bachmann et al. (2013) apply a SVAR model to data from the German Business Climate Survey and the Philadelphia Federal Reserve's Business Outlook Survey to assess the impact of uncertainty on economic activity in Germany and the US, respectively. The paper finds that increases in survey-based uncertainty proxies are associated with significantly less production and employment in both countries over the 1980-2010 period. However, structural analysis suggests that economic responses in Germany and the US differ qualitatively. Namely, uncertainty is found to have more long-lasting negative effects in the US than in Germany. The authors speculate that the prolonged negative response to uncertainty observed in the US may not necessarily be the result of firms undertaking a typical "wait and see" strategy. Alternative explanations revolve around firms' tendency to downsize projects with the aim of minimizing risk of default, agency problems that lead risk-averse business leaders to reduce spending during periods of elevated uncertainty, or international differences in business support.

Ludvigson et al. (2015) also use a SVAR approach, but they propose a new identification strategy to better disentangle the causes and consequences of uncertainty. Namely, the authors distinguish between macroeconomic and financial uncertainty, as well as allow for simultaneous feedback between uncertainty and real economic activity. This is accomplished through the implementation of two shock-based restrictions. In doing so, the paper addresses limitations imposed by the use of recursive ordering, which is widely employed in the existing literature and implicitly assumes that uncertainty causes – but does not contemporaneously respond to – fluctuations in real activity. The paper shows that financial market uncertainty shocks lead to a prominent and persistent decline in real activity while macroeconomic or economic policy uncertainty shocks have no such negative impact. These results are consistent with the theory of "growth options", which states that a mean-preserving rise in risk increases firms' expected profits, which consequently spurs investment and employment. Despite not necessarily causing a reduction in economic activity, the authors conclude that macroeconomic uncertainty plays an important role in exacerbating recessions by amplifying the impacts of output shocks.

A number of other papers put forward similar results using VAR-class models. For instance, Alexopoulos and Cohen (2009) analyze to what extent uncertainty shocks explain business cycle fluctuations. They find that shocks to uncertainty – proxied by a news-based index and a measure of realized stock market volatility – lead to declines in aggregate variables such as industrial production, employment, consumption, and investment. Results, again, suggest that uncertainty is indeed an important contributor to business cycles. In complementary research, Denis and Kannan (2013) employ a low-dimensional VAR model to assess how uncertainty – this time proxied by implied stock market volatility and GDP forecast dispersion – impacts a number of economic indicators in the UK. The authors find that a two standard deviation shock to uncertainty reduces industrial production and GDP by 0.6 and 0.3 percent, respectively. They also show that the peak effects of an uncertainty shock are felt within the months immediately following the shock and ultimately dissipate after a year and a half. The economic impacts of uncertainty are not restricted to developed countries either (Rodrik, 1991). Kang et al. (2020) show that a positive shock to global uncertainty has a negative impact of inflation and interest rates in developing countries such as China, India, and South Africa as well.

In a more recent paper, Baker et al. (2020b) assess how uncertainty is expected to impact US real economic activity in the near-term following the outbreak of COVID-19. In doing so, the authors contribute to a now-large literature focused on analyzing the impacts of pandemic-related economic uncertainty (Baker et al., 2020c; Altig et al., 2020; Leduc & Liu, 2020). Specifically, this paper uses three timely forward-looking uncertainty measures – which were found to rise substantially at the beginning of the pandemic – alongside a VAR model developed by Baker et al. (2020a). The paper finds that around half of the US output contraction forecasted to take place in response to the pandemic can be directly attributed to COVID-induced uncertainty. Similar work by Leduc and Liu (2020) shows that COVID-related uncertainty is also putting downward pressure on US employment and inflation.

Moran et al. (2020) also assess how macroeconomic uncertainty has impacted the real economy during the COVID-19 pandemic. However, this paper focuses specifically on Canada. In fact, by applying the Jurado et al. (2015) method to a large aggregate-level database maintained by Fortin-Gagnon et al. (2020), this paper is the first to construct a robust measure of Canadian macroeconomic uncertainty. This proxy is subsequently employed in the estimation of SVAR models, which show that a shock to US uncertainty of the order of magnitude observed during the pandemic reduced Canadian output, inflation, and investment by 7 percent, 5 percent, and 20 percent, respectively. The effects of a shock to Canadian uncertainty, on the other hand, are found to be shallower and qualitatively different. Namely, the paper concludes that increases in uncertainty originating from the US lead to very pronounced but short-lived impacts on the Canadian economy, while increases in Canadian-borne uncertainty produce less intense but more protracted contractions.

Clearly, significant empirical research has already been conducted to explore the effects of uncertainty on aggregate economic indicators such as output, employment, and inflation.

Research applying similar structural models with the aim of assessing firm-specific responses to uncertainty, however, remains comparatively limited – especially in Canada.

Early work by Leahy and Whited (1996) uses firm-level panel data from Compustat to assess the relationship between uncertainty and investment. This paper proxies uncertainty with variance in daily stock returns and employs a reduced form, rather than structural, modelling approach. It finds that uncertainty decreases investment through its impact on firms' Tobin's *q*. Consistent with real options theory, irreversible investment is purported to be the most likely explanation for the negative relationship identified between uncertainty and investment.

In seminal research, Bloom (2009) investigates the economic impact of large uncertainty shocks such as the Cuban Missile Crisis, the assassination of President Kennedy, and the 9/11 terrorist attacks. The paper first demonstrates how economic indicators respond to uncertainty shocks using a standard SVAR approach on firm-level data. An analysis of impulse response functions shows that industrial production and employment both fall around one percent in response to a one standard deviation shock to uncertainty. These variables then quickly rebound but ultimately overshoot their long-run level in the medium-term. The paper then puts forward a theoretical framework that allows for capital adjustment costs and time varying uncertainty. The model is numerically solved before simulations are used to assess the impact of uncertainty shocks. In line with empirical findings, the theoretical model shows that uncertainty shocks cause a rapid drop, rebound, and overshoot in capital expenditure and hiring. This occurs because an increase in firms' real option value of waiting leads to a build-up of demand for investment and hiring – which is promptly released once uncertainty has receded. Finally, the paper shows that uncertainty pushes down productivity. This occurs because the rate that resources are re-allocated from low to high productivity firms, which is central to the process of creative destruction, slows when employment and investment fall.

Baker et al. (2016) construct a new economic policy uncertainty index – which has now become widely used in the literature – and use it to investigate the impact of policy uncertainty on economic outcomes. This proxy is based on the relative prevalence of uncertainty-related keywords in leading newspapers. By applying panel regressions and VAR models to firm-level data from the Federal Registry of Contracts and Compustat, the paper shows that a US policy uncertainty innovation leads to a 6 percent, 1.1 percent, and 0.35 percent reduction in US gross annual investment, industrial production, and employment. Moreover, the authors show that policy uncertainty is associated with more equity market volatility and larger real economic impacts in policy-sensitive sectors, which are disproportionately affected by changes in government expenditure and regulation. A similar decline in aggregate economic variables is observed when applying a panel VAR framework to 12 major countries – each with its own EPU. Using aggregate economic data, the paper shows that industrial production and employment fall significantly in the months following an upward EPU innovation. A full recovery from the shock is not observed for either economic variable even 36 months after the initial innovation.

Gulen and Ion (2016) also apply Baker et al. (2016)'s news-based economic policy uncertainty index in its assessment of uncertainty shocks. Through the estimation of fixed effects panel regressions and VARs, the authors find that effects of uncertainty are heterogenous and are particularly pronounced for firms whose investments are highly irreversible, as well as for firms that are comparatively more reliant on government expenditure. The paper finds that quarterly investment falls almost 9 percent, relative to average investment in the sample, following a doubling of policy uncertainty. When policy uncertainty remains elevated for an extended period of time, however, the marginal effect it has on investment is lessened. This occurs because the opportunity cost associated with undertaking a "wait and see" strategy begins to outweigh the benefits of delaying investment. Much like in Bloom (2009), investment is shown to rebound strongly but ultimately remains below its pre-shock level for up to 10 quarters, suggesting that the effects of policy uncertainty are persistent. At the same time, overshooting is not found to be a particularly prominent feature of firms' investment response.

3. Data

This paper relies primarily on three types of data to empirically assess the impacts of uncertainty on firm performance. Specifically, it utilizes firm-level financial data for a panel of Canadian and US firms, a range of commonly employed financial, news-based, and firm-specific uncertainty proxies, as well as a number of relevant macroeconomic variables.

3.1. Data-Cleaning Process

Quarterly firm-level accounting data for an unbalanced panel of Canadian and US publicly owned businesses is collected from the Compustat database. This dataset, which spans from 1961Q1 to 2022Q2 at the time of extraction, comprises around 40,000 unique firms and just under 2 million total firm-quarter observations. It includes rich information from firms' cash flow, income, and balance sheet statements. Data from Compustat has been extensively used in the related literature (Baum et al., 2008; Bloom, 2009; Stein & Stone, 2013; Kim, 2020).

We acknowledge that large publicly listed companies, which form the dataset, are not representative of the total population of firms. However, to the best of our knowledge, there do not exist other publicly accessible databases with comparatively comprehensive firm-level data at a similarly high periodicity in Canada. Some alternatives to Compustat include Statistics Canada's Quarterly Survey of Financial Statements (QSFS) and Financial and Taxation Statistics for Enterprises (AFTS). However, both of these surveys collect microdata annual, which was deemed too infrequent to reasonably assess the economic impacts of uncertainty shocks.

The data-cleaning process used in this paper is based on standard practices in the literature (Ottonello & Winberry, 2020; Kim, 2020). The screening performed is especially comprehensive in order to reduce the impact of outliers on parameter estimates and structural analysis.

Young firms, which for the purposes of this paper are characterized as businesses that have been in operation for less than 10 years, are immediately removed.[1] This is done since these firms are still at the start of their lifecycle and therefore tend to have much more volatile sales and investment growth than their more mature counterparts. As such, including young firms in the sample would make it more difficult to isolate the effects of uncertainty on firm performance.

[1] Firm age is defined according to the number of quarters elapsed since the firm's IPO date. If an IPO date is not available, as is most often the case, then firm age is defined as the number of quarters that a firm is listed in the Compustat database.

As is commonly done in the corporate finance literature, we also exclude firms operating in financial services such as banks, insurance companies, and real estate service providers as well as firms in public administration. Next, all firms whose country of incorporation is not listed as Canada or the United States are dropped. Since the database is primarily composed of North American firms, however, doing so removes only a small portion of total firm-quarter observations. Missing values for key accounting variables are imputed using linear interpolation if data is available in both the preceding and successive quarters. We then drop all firm-quarter observations with missing or non-positive values for capital stock, sales, and total assets.

Since the sample period is relatively long, all firm-level accounting variables are appropriately adjusted for inflation using implicit quarterly GDP price deflators. These indices are made available for Canada and the US by the National GDP by Income and Expenditure Accounts and the National Income and Product Accounts, respectively.

Next, we exclude all firms that have undergone significant changes in their organizational composition as a result of a merger or acquisition, for example. This is done since corporate restructuring, which is often undertaken during or following recessions, can lead to significant changes in key performance measures. Failure to consider mergers and acquisitions would make it more difficult to disentangle the impacts of uncertainty shocks from corporate transactions. Since these events are not directly observable in the dataset, however, we choose to exclude firms that experienced a large and sudden change in asset, sales, productivity, or investment growth rates during the study period (Bloom, 2009). Specifically, this entails removing firms with quarter-over-quarter total asset growth, sales growth, productivity growth, or investment rates above the 99.5 percentile and below the 0.5 percentile of their respective distributions.

Finally, we winsorize the sample by dropping firm-quarter observations with implausible values for a number of key financial variables. Specifically, we exclude firm-quarter observations with liquidity[2], leverage[3], cash flow[4], and Tobin's q[5] outside the 0.5-99.5 percentile range. Any firm-quarter observations with leverage above 10 or missing leverage are also removed. In addition, we drop firm-quarter observations with a current asset to total asset ratio higher than 10 or below -10, as well as sales growth above 1 or below -1.

3.2. Firm-Level Performance Measures

The investment rate is calculated as the quarterly log difference in firms' real capital stock, as outlined in (1). The log change in capital stock is used – rather than the ratio of capital expenditure to net capital stock, as is done in Baker et al. (2016) – since recent research has found firm-level capital expenditure to be highly volatile (Jeenas, 2019; Kim, 2020). As is commonly done, firms' capital stock is derived using the perpetual inventory method to correct for the fact

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[2] Liquidity is the ratio of cash and short-term investments to total assets.

[3] Leverage is the ratio of total debt to total assets.

[4] Cash flow is the ratio of operating income before depreciation to book value of capital.

[5] Tobin's q is defined as $q = \frac{Total\ Assets + (Common\ Shares\ Outstandin\ \ \times Share\ Closing\ Price) - Common\ Equity}{Total\ Assets}$.

that property, plant, and equipment is reported at book value rather than replacement value in financial statements (Stein & Stone, 2013).[6]

$$Investment_{i,t} = \log(k_{i,t+1}) - \log(k_{i,t}) \tag{1}$$

Firm-level total factor productivity (TFP) measures the extent to which inputs such as capital, labour, and other intermediate materials are effectively used in production. Firm-level TFP is typically calculated as the residual from a firm-level production function, which – for simplicity – is assumed to have a Cobb-Douglas functional form, as specified in (2). Here, $y_{i,t}$ represents output – proxied by real total revenue – for firm *i* in quarter *t.* Firms are assumed to use capital and labour in production, denoted $k_{i,t}$ and $l_{i,t}$, respectively.[7]

$$y_{i,t} = F_{i,t}(k_{i,t}, l_{i,t}) = k_{i,t}^{\beta_1} l_{i,t}^{\beta_2} \tag{2}$$

The residual is recovered by estimating an empirical Cobb-Douglas production function, as specified in (3). However, rather than using ordinary least squares, which leaves simultaneity bias untreated, we use an approach proposed by Olley and Pakes (1996).[8] This estimation strategy entails using firm-level investment to proxy for unobserved time-varying productivity. In doing so, this two-stage procedure addresses endogeneity arising from the fact that firms will employ more inputs if they experience positive productivity shocks.

$$y_{i,t} = \alpha_{i,t} + \beta_1 \log(k_{i,t}) + \beta_2 \log(l_{i,t}) + \omega_{i,t} + \eta_{i,t} \tag{3}$$

Once the regression is performed, the estimated parameters are subtracted from the outcome variable, as shown in (4). The total residual is composed of productivity, $\omega_{i,t}$, which we are interested in measuring, and an additional term, $\eta_{i,t}$, that can be thought of as measurement error or a shock to productivity (Olley & Pakes, 1996).

$$\widehat{TFP_{i,t}} = \exp(\omega_{i,t}) = \exp(y_{i,t} - \hat{\alpha} - \widehat{\beta_1} \log(k_{i,t}) - \widehat{\beta_2} \log(l_{i,t})) \tag{4}$$

Firm-level productivity growth is then calculated simply by taking the quarter-over-quarter change in firms' TFP, as shown in (5).

$$Productivity\ Growth_{i,t} = \frac{(\widehat{TFP_{i,t}} - \widehat{TFP_{i,t-1}})}{\widehat{TFP_{i,t-1}}} \tag{5}$$

For robustness, productivity is also estimated using ordinary least squares and fixed effects regression models – despite their shortcomings. We generally produce comparable parameter estimates, which lead to similar evaluations of firm-level productivity growth – irrespective of which estimation technique is used (**Table A1**).

The final performance measure of interest, risk of bankruptcy, is measured using the Altman Z-score. It assesses a firm's credit strength by taking a weighted average of five common financial

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[6] Next-period capital stock is defined as $k_{i,t+1} = k_{i,t} + \Delta PPE_t$. Here, $k_{i,t}$ represents the first reported book value of firm *i*'s gross property, plant, and equipment. In each successive period, net investment – equal to the quarter-over-quarter difference in firm *i*'s net property, plant, and equipment – is iteratively added.

[7] Employment is only available at a yearly frequency in Compustat and is therefore quarterly imputed.

[8] The Levinsohn and Petrin (2003) approach – which uses intermediate inputs to proxy for unobserved productivity shocks – has also been widely used to estimate firm-level TFP. However, the Compustat database does not possess firm-level data on intermediate goods such as electricity, materials, or fuels which would be required for its use.

ratios, which are denoted X_n in (6).[9] Broadly, these ratios reflect a firm's liquidity, profitability, operating efficiency, stock price volatility, and total asset turnover.

$$Risk\ of\ Bankruptcy_{i,t} = 1.2X_{1,i,t} + 1.4X_{2,i,t} + 3.3X_{3,i,t} + 0.6X_{4,i,t} + 1.0X_{5,i,t} \quad (6)$$

3.3. Uncertainty Measures

Uncertainty has traditionally been difficult to define and assess. In the past, researchers have used economy-wide measures such as realized and implied stock return volatility, professional forecast dispersion, as well as volatility in equity, bond, and foreign exchange markets to proxy for economic uncertainty (Bloom, 2014). More recently, work conducted by Baker et al. (2016) and Baker et al. (2021) – among others – has led to the construction of new uncertainty indices which apply text analytics to news articles and social media. The use of these aggregate proxies is advantageous because they represent economy-wide uncertainty – which affects all economic agents – rather than just firm-specific idiosyncratic risks. Having said that, cross-sectional uncertainty proxies, such as stock return volatility, remain widely used in the literature as they provide a good proxy for firm-level risks, which have been shown to significantly impact firms' activities (Comin & Philippon, 2005). Accordingly, this paper employs both aggregate and firm-specific measures of uncertainty in its empirical approach, as summarized in **Table 1**.

Table 1: Summary of Uncertainty Measures

Uncertainty Measure	Abbreviation	Type	Source	Period
Canadian Realized Stock Market Volatility	CAN RSMV	Aggregate	Bloomberg	1989Q1-2022Q2
US Realized Stock Market Volatility	US RMSV	Aggregate	FRED	1980Q1-2022Q2
Implied Stock Market Volatility	VIX	Aggregate	FRED	1990Q1-2022Q2
Canadian Economic Policy Uncertainty	CAN EPU	Aggregate	Baker et al. (2016)	1985Q1-2022Q2
US Economic Policy Uncertainty	US EPU	Aggregate	Baker et al. (2016)	1985Q1-2022Q2
Stock Return Volatility	SRV	Firm-Level	Compustat	1980Q1-2022Q2

Note: Some of the above listed uncertainty measures are constructed or made directly available at a daily or monthly frequency. These measures are aggregated to match the quarterly periodicity of the firm-level data.

Realized stock market volatility measures the degree of variation in a country's stock market returns. It is widely used in the existing literature and has previously been shown to be a robust proxy for firm-level uncertainty (Leahy & Whited, 1996; Bloom et al., 2007). In addition, past research has shown this index is highly correlated with other measures of productivity and demand uncertainty (Bloom, 2007). We define realized stock market volatility as the log ratio of the stock market index's intraday high and low, as proposed by Parkinson (1980) and validated by Anderson and Bollerslev (1998). This aggregate uncertainty proxy is calculated for Canada and the US using daily closing prices for the TSX and S&P 500 indices, respectively, as shown in (7).

$$Realized\ Stock\ Market\ Volatility_t = \ln(Index_t^H) - \ln(Index_t^L) \quad (7)$$

We also use option-implied stock market volatility. This widely accepted proxy for macroeconomic uncertainty is represented by the VIX, which is a credit derivative index traded on the Chicago Board Options Exchange (Bloom, 2014). Crucially, implied stock market volatility reflects market participants' perception of volatility in the S&P 500 index over the coming 30 days. That is, unlike realized stock market volatility, option-implied volatility is forward-looking.

[9] See Altman (1968) for details related to the construction and interpretation of the Z-score.

In addition, we employ Baker et al. (2016)'s economic policy uncertainty (EPU) indices for Canada and the US. Broadly, these EPU measures are constructed by using text analytics to track keywords related to policy uncertainty in mainstream media. The Canadian EPU is built by assessing the relative prevalence of uncertainty-related keywords in a number of national newspapers, including the Toronto Star, Vancouver Sun, Montreal Gazette, Ottawa Citizen, and Globe and Mail. The US version of the index is constructed more holistically by incorporating news coverage, as well as tax code expiration data from the Congressional Budget Office and forecaster disagreement from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The number of policy uncertainty keywords detected each month is normalized by the total number of keywords in order to control for time-variant changes in the volume of news. Results from audit studies, as well as comparisons with other text-based and non-policy uncertainty proxies, suggest that this EPU index is a robust proxy for aggregate uncertainty (Baker et al., 2016). We use both Canadian and US EPU indices in this paper since past research has shown that policy uncertainty in a given country can often spill over borders and disrupt real economic activity in other regions (IMF, 2013).

Finally, we employ the most widely used firm-level uncertainty measures: stock return volatility. This proxy differs from the previously discussed aggregate measures in that it reflects idiosyncratic risk, rather than economy-wide uncertainty. Assessing the impacts of a rise in firm-level volatility is of interest since firms' economic activities are predominantly driven by their own outlook and characteristics, rather than aggregate uncertainty (Fiori & Scoccianti, 2021). Moreover, past research has shown that aggregate uncertainty measures do not always move in tandem with firm-level volatility proxies, and can sometimes diverge quite significantly (Comin & Philippon, 2005). Finally, there is evidence to suggest that most of the variation in aggregate uncertainty measures, such as political risk, is driven at the firm-level and should therefore be assessed with a more disaggregated approach (Hassan et al., 2019).

Stock return volatility measures within-quarter dispersion in individual firms' stock returns for all firms $n = 1,2, \dots, N$ in quarter t. It is calculated simply as the average cross-sectional standard deviation of firms' quarterly stock returns, as indicated in (8). Firms' daily adjusted stock closing prices are gathered from the Center for Research in Security Prices (CRSP) database and subsequently matched to firm-level data from Compustat using the global company key.

$$\sigma_{i,t}^{SRV} = \left(\frac{1}{N}\sum_{i=1}^{N}\left(Stock\ Return_{i,t} - \overline{Stock\ Return}_i\right)^2\right)^{1/2} \tag{8}$$

3.4. Macroeconomic Variables

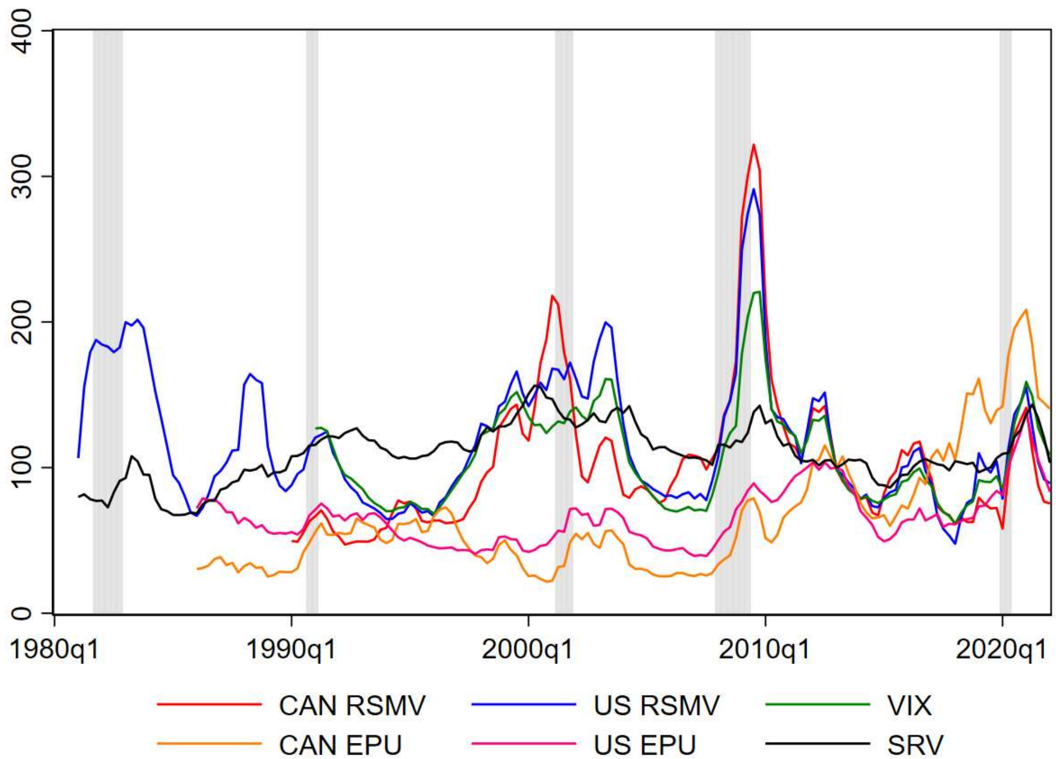
This paper employs the Bank of Canada's Bank Rate as well as the Federal Reserve's Funds Rate. Use of these key short-term monetary policy rates is standard in the literature since the cost of borrowing is well known to have an important influence on investment and other firm activities.

Finally, stock market indices are used to capture market participants' expectations of economic prospects. As surmised by Bloom et al. (2012), proxying for future economic conditions when assessing the impacts of uncertainty helps ease endogeneity concerns arising from the countercyclicality of uncertainty. That is, including the stock market index helps to disentangle the true economic effects of uncertainty from a coincident downturn in the business cycle. This paper uses the TSX and S&P 500 indices to proxy for market conditions in Canada and the US, respectively.[10] Daily data is drawn from Bloomberg and subsequently aggregated.

3.5. Descriptive Statistics

The sample is restricted to the period 1980Q1-2022Q1 and thus includes several business cycle episodes. The fully processed dataset contains 9,273 distinct firms and 366,146 total firm-quarter observations. Descriptive statistics for all of the key accounting variables, uncertainty measures, and other macroeconomic series used in this paper are presented in **Tables 2**-**4**, respectively. In general, we find that the Canadian and US subsamples are reasonably comparable along many dimensions. However, we note that US firms tend to be larger, more mature, and more levered than their Canadian counterparts. The three outcome variables of interest: investment rates, productivity growth, and risk of bankruptcy are plotted, by country, in **Figures A1-A3**. The sectoral distribution of the sample's firms is highlighted in **Table A2**.

Figure 2: Uncertainty Measures



Note: All uncertainty measures are expressed as 4-quarter moving averages and are indexed such that 2013Q1 = 100. Stock return volatility is weighted by firms' average total assets over the sample period. Consult the Data section for a complete description of all uncertainty measures. Shaded regions denote US recessions, as defined by the National Bureau of Economic Research.

Unsurprisingly, we find that measures of uncertainty are inversely correlated with firm-level investment rates, productivity growth, and bankruptcy risk (**Table A3**). Consistent with what we know about how uncertainty is related to the business cycle, all of the uncertainty proxies are also shown to increase during economic recessions and fall during the ensuing expansions (**Figure**

[10] Gulen and Ion (2016) use one-year-ahead forecasts of GDP growth to proxy for investment opportunities. Although these historical forecasts can be calculated for the US using publicly accessible data from the Philadelphia Federal Reserve's Livingstone Survey, comparable vintage forecasts are not available for Canada over the sample period.

2). In addition, we note that firm-level uncertainty, proxied by stock market volatility, is less volatile than economy-wide measures. This suggests that large, publicly traded non-financial firms may be less affected by uncertainty than what is perceived more broadly in the economy.

Table 2: Descriptive Statistics for Firm-Level Variables

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Panel A: Canada (Firms = 1,454, n = 36,017)						
Firm Age	84.09	33.60	40	192	0.85	3.15
Total Assets	21,580	22,687	0	159,671	2.09	9.68
Sales Growth	0.014	0.202	-0.999	0.999	-0.07	7.06
Liquidity	0.053	0.074	0	0.903	3.42	19.91
Cash Flow	0.091	0.230	-16.63	4.16	-6.43	523.10
Leverage	0.328	0.167	0	2.381	-0.42	4.20
Tobin's q	1.426	0.575	0.463	12.755	3.47	29.86
Investment Rate	0.012	0.810	-0.631	0.835	2.23	30.77
Productivity Growth	0.027	0.217	-0.654	1.746	1.76	12.66
Altman Z-Score	1.524	2.443	-225.01	78.541	5.87	358.00
Panel B: US (Firms = 7,819, n = 330,129)						
Firm Age	99.20	42.61	40	216	0.52	2.21
Total Assets	51,669	80,284	0	559,544	2.66	10.90
Sales Growth	0.013	0.164	-0.999	0.999	-0.26	8.69
Liquidity	0.081	0.112	0	0.904	2.67	11.62
Cash Flow	0.166	0.307	-16.71	4.16	-4.92	342.81
Leverage	0.307	0.172	0	2.383	1.24	8.91
Tobin's q	1.703	1.054	0.462	12.740	3.52	21.06
Investment Rate	0.009	0.074	-0.635	0.841	2.28	35.36
Productivity Growth	0.020	0.177	-0.658	1.796	1.68	14.72
Altman Z-Score	2.159	2.863	-237.421	80.167	3.52	84.02

Note: Total assets are expressed in Canadian and US dollars for Canadian and US firms, respectively. All accounting variables have been appropriately adjusted for inflation using country-specific deflators. All variables have been weighted by average total assets over the sample period. Consult the Data section for a complete description of all firm-level variables

Table 3: Descriptive Statistics for Uncertainty Measures

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
CAN RSMV	165.01	97.94	59.14	830.60	3.26	19.61
US RSMV	154.86	76.98	59.58	643.77	2.58	14.39
VIX	144.32	53.31	76.20	433.12	1.91	9.52
CAN EPU	58.27	39.51	11.65	220.59	1.52	5.30
US EPU	92.32	32.24	45.78	226.63	1.21	4.69
SRV	97.09	21.38	19.74	195.53	0.52	3.90

Note: All uncertainty measures are indexed such that 2013Q1 = 100. Consult the Data section for a complete description of all uncertainty measures.

Table 4: Descriptive Statistics for Macroeconomic Variables

Variable	Mean	SD	Min	Max	Skewness	Kurtosis
Bank of Canada Bank Rate	0.048	0.039	0.005	0.202	1.14	3.88
Federal Reserve Fund Rate	0.039	0.035	0.001	0.178	1.10	4.64
TSX Index	877	484	150	2,131	0.33	2.00
S&P 500 Index	1,190	898	108	4,602	1.39	5.24

3.6. Stationarity Properties

To explore whether variables in the prepared dataset are stationary, we conduct Augmented Dickey-Fuller panel unit root tests. This procedure's null hypothesis states that all panels contain a unit root. Results from the test are shown in **Table 5**. Since we cannot reject the tests' null hypothesis for all variables, we conclude that some series are non-stationary in level and must therefore be transformed prior to model estimation.

Table 5: Panel Unit Root Test Results

Variable	Test Statistic	p-Value	Conclusion	Required Transformation
Panel A: Firm-Level Variables				
Firm Age	-80.393***	0.00	Stationary	None
Firm Size	-296.88***	0.00	Stationary	None
Sales Growth	-314.29***	0.00	Stationary	None
Liquidity	-293.08***	0.00	Stationary	None
Cash Flow/Total Assets	-316.58***	0.00	Stationary	None
Leverage	-318.33***	0.00	Stationary	None
Tobin's *q*	-292.81***	0.00	Stationary	None
Investment Rate	-323.50***	0.00	Stationary	None
Productivity Growth	-303.33***	0.00	Stationary	None
Altman's Z-Score	-257.69***	0.00	Stationary	None
Panel B: Uncertainty Measures				
CAN RSMV	-3.59***	0.00	Stationary	None
US RSMV	-5.73***	0.00	Stationary	None
VIX	-4.15***	0.00	Stationary	None
CAN EPU	-4.89***	0.00	Stationary	None
US EPU	-5.28***	0.00	Stationary	None
SRV	-3.58**	0.03	Stationary	None
Panel C: Macroeconomic Variables				
Bank of Canada Bank Rate	-3.17*	0.09	Stationary	None
Federal Reserve Fund Rate	-3.63**	0.03	Stationary	None
TSX Index	-2.34	0.43	Non-Stationary	First Difference
S&P 500 Index	-2.46	0.99	Non-Stationary	First Difference

Note: Lag length is set to 4. Test statistic is the result of an Augmented Dickey Fuller test with drift and trend components. Firm size is measured as total assets. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

4. Methodology

We begin our assessment of the firm-level economic impacts of uncertainty by performing panel regressions. This approach is commonly employed in the related literature as it enables us to quantify the effects of uncertainty on firm performance while concurrently controlling for unobserved factors. Moreover, panel regressions allow us to explore heterogeneity in firm-level responses to uncertainty. This is especially useful since we are interested in assessing how economic impacts differ for firms of different size and age. If real option, precautionary saving, and credit constraint effects are prominent, we would likely expect to see smaller and younger firms be more strongly affected by uncertainty (Senga, 2015). The use of panel regressions also allows us to answer related empirical questions, such as to what extent Canadian and US firms respond differently to domestic and international uncertainty, and whether the effects of policy uncertainty overshadow the impacts of more conventional financial market volatility.

The economic impacts of uncertainty are subsequently analyzed with a VAR approach. This econometric technique is better suited to modelling dynamic relationships since it allows endogenously specified variables to depend on their own lags, as well as the lags of other variables in the system. In addition, VAR models allow for multiple variables to be treated endogenously – and therefore do not require the econometrician to specify a single outcome of interest. This is particularly important in a macroeconomic context, where true exogeneity is more difficult to justify. For these two reasons, VAR modelling is more flexible than conventional panel approaches such as pooled OLS, fixed effect, or random effect regressions. Moreover, we note that VARs – as a result of being widely employed in the existing uncertainty literature – allow results from this paper to be more easily compared with those obtained from past research. Maybe most crucially, however, is the competitive advantage VARs possess in modelling the transmission of shocks. Through the assessment of variance decomposition and impulse response functions, this approach enables us to quantitatively and qualitatively assess whether, in what way, and for how long uncertainty innovations affect firm-level outcomes.

4.1. Panel Regression Specification

The panel regression specifications used in this section are inspired by the fixed effect models estimated by Gulen and Ion (2016), Handley and Li (2020), as well as Kim (2020).

$$Perf^{K}_{i,c,t} = \alpha + \beta_1 Unc^{L}_{t} + \beta_2\left(Unc^{L}_{t} \times Age_{i,c,t-1}\right) + \beta_3\left(Unc^{L}_{t} \times Size_{i,c,t-1}\right) + \Psi X_{i,c,t-1} + QRT_t + \mu_i + \lambda_{c,t} + \epsilon_{i,c,t} \qquad (9)$$

In (9), the primary coefficient of interest, β_1, describes the relationship between uncertainty and firm performance measure *K* for firm *i* in country *c* and quarter *t*. Since we are also interested in assessing heterogeneity in the impacts of uncertainty, we include two additional terms which interact uncertainty with age and size, respectively. As such, the coefficients β_2 and β_3 reflect how the impact of uncertainty on a firm's investment rate, productivity growth, and risk of bankruptcy is affected as its age and size are varied. The vector $X_{i,t-1}$ includes lagged firm age, size, and sales growth. Finally, we specify fiscal quarter, firm, and country-by-date fixed effects to control for seasonality, unobserved time-invariant firm characteristics, and time-varying country-specific dynamics, respectively.

$$Perf^{K}_{i,c,t} = \alpha + \beta_1 Unc^{L}_{t} + \beta_2\left(Unc^{L}_{t} \times Age_{i,c,t-1}\right) + \beta_3\left(Unc^{L}_{t} \times Size_{i,c,t-1}\right) + \Psi X'_{i,c,t-1} + \theta Y_{c,t} + QRT_t + \mu_i + \lambda_{c,t} + \epsilon_{i,c,t} \qquad (10)$$

A second, more comprehensive specification, (10), is also employed. All of the same fixed effects used in the baseline regression are also included in this augmented specification. In addition to lagged age, size, and sales growth, $X'_{i,c,t-1}$ now includes controls for other pertinent firm-level characteristics including prior-period leverage, operating cash flow, and Tobin's *q* – the latter of which is included to proxy for firm-specific investment opportunities. A vector of contemporaneous economy-wide controls, $Y_{c,t}$, includes the monetary policy rate and stock market index for country *c* in quarter *t*. The former is used to represent cost of borrowing while the latter is specified to reflect economic conditions and financial market sentiment. As previously mentioned, use of the stock market index also helps alleviate endogeneity concerns stemming from the fact that uncertainty, as a result of being notably countercyclical, is strongly correlated with expectations of poor economic prospects (Bloom et al., 2012; Denis & Kannan, 2013; Gulen & Ion, 2016; Jurado et al., 2016). In addition, $Y_{c,t}$ includes an indicator variable representing prime ministerial and presidential election years for Canada and the US, respectively. We control for national elections since past research has found that firm-level activity falls significantly in election years, even after controlling for growth opportunities and economic conditions (Julio & Yook, 2012).

We speculate that "wait and see" dynamics cause $\beta_1 < 0$. That is, higher uncertainty – whether proxied by aggregate or firm-specific volatility measures – should have a direct negative effect on all measures of firm performance. In addition, we predict that $\beta_2 > 0$ and $\beta_3 > 0$ since past research has shown that more mature and larger firms are somewhat more insulated from the negative effects of uncertainty (Fiori & Scoccianti, 2021).

All of the panel regression models estimated in this section are weighted by firms' average total assets over the sample period. To facilitate interpretability and account for differences in the construction of the uncertainty measures as well as the units of measurement used in firm-level outcomes, all of the specified variables are standardized to have a mean of 0 and standard deviation of 1. Robust standard errors are clustered at the firm level. Since date fixed effects are used, clustering standard errors on the firm dimension alone – rather than using two-way clustering – is sufficient to ensure that standard errors are unbiased (Petersen, 2005).

4.2. VAR Specification

We now turn to the estimation of VAR-class models. Rather than using a panel VAR (PVAR) framework to assess the impacts of uncertainty shocks, we employ a bottom-up approach which entails aggregating firm-level data into quarterly time series. The VAR model specified in (11) serves as the framework for assessing the impact of uncertainty on firm outcomes. Variable selection is largely inspired by Gulen and Ion (2016). This VAR can be loosely thought of as the multivariate extension of the previously specified augmented panel regression framework and is estimated separately for Canadian and US samples.

$$Y_{i,c,t} = \alpha + \sum_{j=1}^{p} \Gamma_j Y_{i,c,t-j} + \Psi_t X_{c,t} + \epsilon_{i,c,t} \tag{11}$$

$$\text{where } Y_{i,c,t} = \begin{bmatrix} Uncertainty_{c,t}^{L} \\ Sales\ Growth_{i,c,t} \\ Cash\ Flow_{i,c,t} \\ Performance_{i,c,t}^{K} \\ Monetary\ Policy\ Rate_{c,t} \\ Stock\ Market\ Index_{c,t} \\ Tobin's\ q_{i,c,t} \end{bmatrix} \text{ and } X_{c,t} = \begin{bmatrix} Fiscal\ Quarter_t \\ Election\ Year_{c,t} \end{bmatrix}$$

$Y_{i,c,t}$ is a 7×1 vector that includes a number of endogenously specified variables for firms *i* in country *c* and quarter *t*. We include one of the six uncertainty proxies, *L*, discussed above. As is done in the previously estimated augmented fixed effects model, sales growth, cash flow, and Tobin's *q* are used to control for firms' financial characteristics and investment opportunities. These variables are constructed by taking weighted cross-sectional averages of firm-level sales growth, cash flow, and Tobin's *q*, respectively. We include one of the three key firm performance measures used in this paper, denoted by *K*. The monetary policy rate, as set by country *c*'s central bank, is also included as an endogenous variable since interest rates are changed in response to – and have an important effect on – economic conditions and firm activity (Benati, 2014). The country-specific stock market index is used because uncertainty and financial markets are well known to be dynamically related. Use of financial market indices in uncertainty VAR modelling can be found in Bloom (2009) and Jurado et al. (2015). For simplicity, variable selection is not changed for each firm performance being studied.

$X_{c,t}$ is a 2×1 exogenous vector that specifies two dummy variables for fiscal quarters and election years. As before, this is done to control for seasonality and the fact that firms may exhibit different behavior around national elections. α is a 7×1 vector of intercept terms while $\epsilon_{i,c,t}$ is a 7×1 vector of error terms, which are assumed to be independent and identically distributed.

The optimal number of lags, *p*, is selected using the Schwarz information criteria (SIC). To control the number of parameters to estimate, the maximum permittable number of lags is set to 8. However, the information criteria is typically found to be minimized when a model includes just a couple lags of the endogenous variables. The SIC is used rather than the Akaike information criteria (AIC) as a result of its parsimonious tendency to select fewer lags.

Exploratory analysis reveals that there are no significant cointegrating relationships among endogenous variables. In fact, with the exception of the stock market index variable, all of the specified variables are stationary in level terms. At the same time, the selected model does not have an exceedingly large number of parameters to estimate, relative to degrees of freedom. As such, this paper proceeds with the estimation of a standard VAR, rather than a vector error correction model or Bayesian VAR.

4.3. Shock Identification

We first estimate an unrestricted VAR and subsequently impose exclusion restrictions to structuralize the model. As is commonly done in the existing literature, shocks in the SVAR are identified using a Cholesky decomposition. This approach requires us to make timing assumptions about how variables in the system are related, and consequently, how shocks are propagated. Practically, this means specifying variables in decreasing order of exogeneity – as is done in (11). As such, the variable ordered first in the system is presumed to not be contemporaneously affected by other endogenous variables, but remains affected by its own lags as well as the lags of other variables. Conversely, the variable ordered last is implicitly assumed to not contemporaneously affect other variables, but is again influenced by its own lags as well as the lags of other variables in the system.

The uncertainty proxy is ordered first since it is assumed to affect all other endogenously specified variables contemporaneously. The same approach is taken by Bachman et al. (2013), who recursively orders uncertainty before a measure of economic activity in a bivariate VAR, as well as Alexopoulos and Cohen (2009), who place the uncertainty proxy first in their multivariate VAR ordering. Sales growth is specified next since uncertainty is assumed to affect demand in the same period. This ordering is consistent with precautionary savings theory, which postulates that households reduce their consumption in response to uncertainty over the future. Naturally, we order firms' cash flow next since a change to sales directly impacts companies' operating revenue. This choice is also consistent with research from Çolak et al. (2020), which finds a significant causal link between uncertainty indicators and businesses' balance sheet strength. Firm performance – whether measured by investment rates, productivity growth, or bankruptcy risk – is ordered next. By doing so, we assume that firms set their capital expenditure plans and choose their input mix in response to their perceived degree of economic uncertainty as well as their own financial standing. We assume that firm-level outcomes are not contemporaneously affected by monetary policy rates – which are ordered next. This is done since central bank actions are well known to only affect economic activity several quarters after they are taken. By proceeding with this recursive ordering, we remain consistent with the traditional assumption that changes to interest rates contemporaneously affect prices, but not quantities. A similar approach is taken by Bloom (2009) as well as Alexopoulos and Cohen (2009). The stock market index, expressed as a log-difference, follows since we assume that uncertainty shocks, firm-level characteristics, and interest rates all instantaneously impact financial markets – which are viewed as efficient and therefore quick to incorporate news. By doing so, however, we implicitly assume that financial markets contemporaneously respond to – but do not cause – uncertainty shocks. This is contrary to the identification strategy used in Bloom (2009), which instead assumes that uncertainty is a byproduct of financial market fluctuations. Finally, we specify firms' Tobin's *q.* This timely and comprehensive measure of firm-level investment opportunities is assumed to be affected contemporaneously by all of the previously specified endogenous variables.

The recursive ordering chosen seems sensible and is broadly in line with the existing literature. However, since there is no single, obvious, or empirically established way of ordering the model's endogenous variables – and because it is well known that IRFs are sensitive to the specified variable ordering – we also employ various alternative specifications. In particular, we examine to what extent impulse response functions change if the uncertainty proxy is ordered differently – and whether uncertainty has any effect on firm performance at all when placed last in the recursive ordering. For added robustness, we also employ generalized impulse response functions (GIRFs) which are order-invariant and are thus not susceptible to the often-subjective ordering imposed by the modeler (Koop et al., 1996).

5. Results

In this section, we begin by presenting regression results from the estimated panel regression models. We then highlight findings from the SVARs. Since the interpretation of regression coefficients is typically not of greatest interest when working with VAR-class models, however, we focus primarily on performing structural analysis – which entails assessing the models' variance decomposition and impulse response functions.

5.1. Panel Regression Results

Panel regression results are shown in **Tables 8-10**. Consistent with *a priori* expectations and findings from the related literature, we show that higher uncertainty is related with worse firm-level outcomes. Since predictor variables are standardized, all of the estimated coefficients can be interpreted as the standard deviation change associated with a one standard deviation increase in the corresponding explanatory variable.

We find that a one standard deviation increase in uncertainty, holding all else constant, is related with nearly a 0.23 standard deviation decrease in firm-level investment rates, on average. This is equivalent to a 1.7 percent decrease in investment rates, which is economically meaningful given that the weighted mean quarterly investment rate for firms in the sample is 0.94 percent. In addition, the relation between uncertainty and investment rates is generally found to be statistically significant at conventional levels and is not found to diminish or qualitatively change when controlling for additional firm-level characteristics, suggesting that parameter estimates are reasonably robust. We find little difference between the impacts of economic policy uncertainty and financial market volatility. That is, an increase in realized or implied stock market volatility is found to have a comparable effect on firm-level investment rates as a rise in Canadian or US economic policy uncertainty. Furthermore, there does not seem to be any discernible difference between the effects of economy-wide and firm-level volatility.

When productivity growth is specified as the firm-level outcome of interest, the direct impact of uncertainty is again found to be negative but the estimated parameters are no longer statistically significant. A one standard deviation increase in uncertainty is now related with a 0.06 standard deviation decrease in productivity growth, on average, holding all else equal. This is equivalent to a 1.1 percent decrease in TFP growth – which we again recognize as being meaningful given that the mean productivity growth rate for firms in the sample, weighted by average assets, is 2 percent. We note that increases in US RSMV and VIX are not associated with lower productivity growth. In addition, unlike economy-wide uncertainty measures, firm-level uncertainty is not found to reduce TFP growth. This suggests that firms are largely looking through volatility in their own stock price when making decisions about labour and capital utilization, but face greater challenges making efficient use of inputs when uncertainty is broad-based.

Although qualitatively consistent with results from Bloom (2009) or Alexopoulos and Cohen (2009) – which both show a strongly negative association between uncertainty and the level of productivity – findings in this paper generally point to a weaker and sometimes positive relationship between uncertainty and productivity growth. This is consistent with a strand of the uncertainty literature which suggests that the relationship between these variables may not necessarily be unidirectionally negative. For instance, Nguyen et al. (2021) demonstrate that economic policy uncertainty acts like an exogenous shock that harms poorly run businesses while concurrently creating opportunities for talented entrepreneurs. In this way, uncertainty spurs creative destruction and fosters an increase in aggregate productivity. Research by Choi et al. (2016), on the other hand, shows that the impacts of uncertainty on productivity growth are much larger for credit-constrained firms or businesses in industries that are reliant on external financing. This constraint may not necessarily be binding for many of the businesses in the sample of relatively mature, large, and non-financial publicly traded firms studied in this paper.

When the Altman Z-score is specified as the firm-level outcome, uncertainty is found to have a mostly statistically significant association with firms' bankruptcy risk. On average, a one standard deviation increase in uncertainty is related with a 0.01 standard deviation decline in Altman Z-scores. Although seemingly small, this is equivalent to a 0.28 point reduction in firms' Z-score – which is economically meaningful considering that the mean Altman Z-score in the sample, weighted by firms' average assets, is 2.10. For reference, bankruptcy risk is considered elevated for firms with a Z-score below 1.80 (Altman, 1968). We note that Canadian economic policy uncertainty and firm-specific stock return volatility are not found to have statistically significant effects on firms' bankruptcy risk.

Table 8: Investment Rate

Variable	CAN RSMV		US RSMV		VIX		CAN EPU		US EPU		SRV	
Unc	-.322***	-.441*	-.141***	-.140**	-.587**	-.193	-.085	-.163*	-.116**	-.129**	-.232***	-.251***
	(.094)	(.268)	(.053)	(.060)	(.233)	(.157)	(.089)	(.101)	(.058)	(.061)	(.063)	(.078)
$Unc \times Size$	.065*	.034	.054***	.023	.040	-.022	-.078***	-.005	-.024	-.001	.110***	.093
	(.034)	(.031)	(.020)	(.042)	(.038)	(.046)	(.029)	(.034)	(.026)	(.030)	(.033)	(.076)
$Unc \times Age$	.117**	.131*	.080	.093	.115**	.145*	.116	.125	.110**	.093	.132	.167
	(.059)	(.071)	(.062)	(.081)	(.058)	(.078)	(.083)	(.106)	(.050)	(.063)	(.085)	(.111)
$Size$	-.241***	-.187***	-.237***	-.184***	-.241***	-.157***	-.183***	-.177***	-.199***	-.178***	-.313***	-.255***
	(.043)	(.037)	(.037)	(.035)	(.055)	(.049)	(.040)	(.040)	(.046)	(.045)	(.047)	(.062)
Age	-.102***	-.078	-.095***	-.074	-.105***	-.086*	-.074**	-.033	-.088***	-.054	-.143***	-.134**
	(.038)	(.052)	(.035)	(.047)	(.038)	(.050)	(.034)	(.050)	(.033)	(.047)	(.049)	(.062)
$Sales\ Growth$	-.008	-.007	-.009	-.008	-.008	-.006	-.010	-.009	-.010	-.009	-.006	-.007
	(.011)	(.006)	(.009)	(.006)	(.011)	(.006)	(.010)	(.006)	(.010)	(.006)	(.008)	(.006)
$Cash\ Flow$		.194***		.193***		.194***		.192***		.192***		.205***
		(.050)		(.050)		(.050)		(.050)		(.050)		(.056)
$Leverage$		-.100***		-.092***		-.098***		-.100***		-.101***		-.083***
		(.020)		(.017)		(.020)		(.019)		(.018)		(.022)
$Tobin's\ Q$		.088***		.087***		.090***		.087***		.086***		.086***
		(.018)		(.017)		(.017)		(.017)		(.017)		(.018)
$Monetary\ Policy\ Rate$		.955		-.004		.100		.030		.048		-.030
		(.0966)		(.029)		(.064)		(.056)		(.056)		(.027)
$Stock\ Market\ Index$		-.220***		-.097***		.078		-.155***		-.157***		-.074***
		(.062)		(.029)		(.127)		(.044)		(.044)		(.017)
$Election\ Year$		.056***		.040**		.051**		.043**		.045**		.049**
		(.021)		(.020)		(.021)		(.018)		(.018)		(.022)
n	300,164	250,606	326,999	269,551	294,992	246,874	322,255	265,866	322,255	265,866	310,526	256,083
R^2	.000	.002	.000	.012	.000	.013	.000	.012	.000	.012	.000	.011
$Period$	1989Q1-2022Q1	1989Q1-2022Q1	1980Q2-2022Q1	1980Q2-2022Q1	1990Q1-2022Q1	1990Q1-2022Q1	1985Q1-2022Q1	1985Q1-2022Q1	1985Q1-2022Q1	1985Q1-2022Q1	1980Q2-2022Q1	1980Q2-2022Q1

Note: All variables are standardized to have mean of 0 and standard deviation of 1. All firm-level accounting variables have been appropriately adjusted for inflation. Firm size is measured as the logarithm of total assets. The stock market index variable is expressed as a logarithmic first difference. Firm-level controls such as size, age, sales growth, cash flow, leverage, and Tobin's q are lagged one quarter. Consult the Data section for a complete description of all firm-level variables and uncertainty measures. Each specification includes firm, fiscal quarter, and $country \times date$ fixed effects. Regressions are weighted by average total assets over the sample period. Robust standard errors, clustered at the firm level, are shown in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 9: Productivity Growth

Variable	CAN RSMV		US RSMV		VIX		CAN EPU		US EPU		SRV	
Unc	-.015 (.070)	-.972*** (.293)	.037 (.043)	.038 (.059)	.286** (.140)	-.216 (.208)	-.002 (.058)	-.020 (.075)	-.058 (.037)	-.071* (.043)	.132 (.088)	.137 (097)
$Unc \times Size$	-.048** (.020)	-.036 (.025)	-.028* (.016)	-.018 (.021)	-.006 (.019)	-.001 (.026)	-.020* (.012)	-.035* (.017)	-.014 (.017)	-.016 (.020)	.051 (.044)	.007 (.042)
$Unc \times Age$	.007 (.053)	.001 (.069)	-.016 (.045)	-.016 (.060)	-.030 (.049)	-.020 (.063)	.052 (055)	.052 (.073)	.092** (.040)	.115** (.047)	-.103 (.098)	-.054 (.108)
$Size$	-.020 (.018)	.015 (.025)	-.036** (.017)	-.001 (.023)	-.039* (.021)	-.004 (.029)	-.041** (.017)	.007 (.073)	-.040** (.019)	.003 (.024)	-.096** (.040)	-.019 (.038)
Age	-.011 (.018)	-.005 (.028)	-.004 (.016)	.007 (.024)	-.002 (.020)	-.000 (.029)	-.002 (.014)	.003 (.023)	-.016 (.015)	-.010 (.023)	.038 (.044)	.027 (.052)
$Sales\ Growth$	-.224*** (.013)	-.213*** (.015)	-.225*** (.013)	-.210*** (.015)	-.223*** (.013)	-.212*** (.015)	-.226*** (.013)	-.212*** (.015)	-.226*** (.013)	-.211*** (.015)	-.233*** (.013)	-.217*** (.015)
$Cash\ Flow$		-.217*** (.046)		-.232*** (.048)		-.215*** (.046)		-.230*** (.047)		-.230*** (.047)		-.233*** (.051)
$Leverage$		.081*** (.009)		.066*** (.009)		.082*** (.009)		.067*** (.009)		.067*** (.009)		.068*** (.009)
$Tobin's\ Q$		.043*** (.009)		.042*** (.009)		.043*** (.009)		.042*** (.009)		.042*** (.009)		.044*** (.009)
$Monetary\ Policy\ Rate$		3.311*** (1.034)		-.500*** (.019)		-.090 (.062)		-.211*** (.056)		-.185*** (.053)		.038 (.028)
$Stock\ Market\ Index$		.346*** (.072)		.048*** (.017)		-.157 (.169)		.073*** (.018)		.073*** (.018)		.050*** (.017)
$Election\ Year$		.031*** (.011)		.026*** (.010)		.021* (.011)		.023** (.010)		.020** (.010)		.031*** (.010)
n	277,297	234,342	303,027	252,605	272,316	230,712	298,421	249,012	298,421	249,012	293,376	244,654
R^2	.044	.000	.045	.047	.038	.500	.044	.041	.044	.041	.051	.055
$Period$	1989Q1- 2022Q1	1989Q1- 2022Q1	1980Q2- 2022Q1	1980Q2- 2022Q1	1990Q1- 2022Q1	1990Q1- 2022Q1	1985Q1- 2022Q1	1985Q1- 2022Q1	1985Q1- 2022Q1	1985Q1- 2022Q1	1980Q2- 2022Q1	1980Q2- 2022Q1

Note: All variables are standardized to have mean of 0 and standard deviation of 1. All firm-level accounting variables have been appropriately adjusted for inflation. Firm size is measured as the logarithm of total assets. The stock market index variable is expressed as a logarithmic first difference. Firm-level controls such as size, age, sales growth, cash flow, leverage, and Tobin$'s\ q$ are lagged one quarter. Consult the Data section for a complete description of all firm-level variables and uncertainty measures. Each specification includes firm, fiscal quarter, and $country \times date$ fixed effects. Regressions are weighted by average total assets over the sample period. Robust standard errors, clustered at the firm level, are shown in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Table 10: Altman Z-Score

Variable	CAN RSMV		US RSMV		VIX		CAN EPU		US EPU		SRV	
Unc	-.090***	-.077***	-.053**	-.053***	.481*	-.096***	-.052	-.054	-.082***	-.058**	-.016	-.006
	(.021)	(.029)	(.021)	(.020)	(.268)	(.030)	(.054)	(.041)	(.028)	(.027)	(.033)	(.026)
$Unc \times Size$	.036***	.005	.047**	.004	.058**	.002	-.046	-.000	-.030	-.012	.088*	-.006
	(.014)	(.005)	(.019)	(.007)	(.024)	(.009)	(.030)	(.023)	(.029)	(.024)	(.048)	(.019)
$Unc \times Age$	.030	.051***	.007	.049	-.003	.047	.103***	.046	.111**	.065	-.074	.011
	(.022)	(.016)	(.035)	(.025)	(.049)	(.033)	(.040)	(.042)	(.049)	(.043)	(.076)	(.040)
$Size$	-.106***	-.004	-.108***	-.003	-.130***	-.003	-.058*	-.002	-.059*	.007	-.160***	.006
	(.031)	(.021)	(.031)	(.020)	(.035)	(.021)	(.031)	(.022)	(.032)	(.025)	(.052)	(.025)
Age	-.141**	-.114***	-.131**	-.112***	-.133**	-.116***	-.126*	-.094**	-.142*	-.107**	-.099**	-.105***
	(.070)	(.040)	(.063)	(.038)	(.062)	(.039)	(.073)	(.0040)	(.074)	(.042)	(.047)	(.033)
$Sales\ Growth$	.006***	-.000	.006**	-.000	.006***	-.000	.006***	-.000	.006***	-.000	.005***	-.000
	(.001)	(.002)	(.001)	(.002)	(.001)	(.002)	(.001)	(.002)	(.001)	(.002)	(.001)	(.002)
$Cash\ Flow$		.068*		.067*		.068*		.067*		.067*		.068
		(.039)		(.039)		(.039)		(.039)		(.039)		(.042)
$Leverage$		-.136***		-.132***		-.137***		-.132***		-.132***		-.130***
		(.011)		(.010)		(.011)		(.010)		(.010)		(.010)
$Tobin's\ Q$		.194***		.194***		.194***		.194***		.194***		.198***
		(.018)		(.018)		(.018)		(.018)		(.018)		(.018)
$Monetary\ Policy\ Rate$		.030		.006		-.085***		-.004		-.007		.006
		(.091)		(.004)		(.031)		(.006)		(.006)		(.004)
$Stock\ Market\ Index$		.016**		-.011**		-.025**		.007**		.008***		-.007*
		(.007)		(.004)		(.012)		(.004)		(.003)		(.004)
$Election\ Year$		.008		.006		.008		.007		.008		.007
		(.006)		(.006)		(.006)		(.006)		(.006)		(.006)
n	209,686	197,478	215,409	202,028	208,618	196,559	214,700	201,379	214,700	201,379	203,681	191,174
R^2	.004	.094	.004	.097	.009	.098	.005	.102	.001	.101	.002	.116
$Period$	1989Q1-2022Q1	1989Q1-2022Q1	1980Q2-2022Q1	1980Q2-2021Q2	1990Q1-2022Q1	1990Q1-2022Q1	1985Q1-2022Q1	1985Q1-2022Q1	1985Q1-2022Q1	1985Q1-2022Q1	1980Q2-2022Q1	1980Q2-2022Q1

Note: All variables are standardized to have mean of 0 and standard deviation of 1. All firm-level accounting variables have been appropriately adjusted for inflation. Firm size is measured as the logarithm of total assets. The stock market index variable is expressed as a logarithmic first difference. Firm-level controls such as size, age, sales growth, cash flow, leverage, and Tobin's q are lagged one quarter. Consult the Data section for a complete description of all firm-level variables and uncertainty measures. Each specification includes firm, fiscal quarter, and $country \times date$ fixed effects. Regressions are weighted by average total assets over the sample period. Robust standard errors, clustered at the firm level, are shown in parentheses. ***, **, and * denote statistical significance at the 1, 5, and 10 percent levels, respectively.

Next, we explore heterogeneity across firm age and size. Irrespective of which firm performance measure is specified as the dependent variable, we see that the interaction of age and uncertainty is generally positive but not always statistically significant. This result suggests that the adverse effects of uncertainty are dampened somewhat for more mature firms. Consider that a one standard deviation increase in firm age reduces the impact of uncertainty on investment growth by approximately 0.12 standard deviations. Then, a company that is one standard deviation older than the average firm in the sample – holding all else equal – experiences around half the impact from uncertainty on investment growth as a firm of average age. This coefficient falls to 0.04 when bankruptcy risk is specified as the dependent variable and just 0.01 when productivity growth is the outcome of interest. The interaction of uncertainty and size, on the other hand, is found to be smaller and typically not statistically significant. In fact, this parameter is estimated to be just 0.02 when the outcome of interest is firm-level investment rates. When productivity growth or risk of bankruptcy is specified as the dependent variable, the interaction of age and uncertainty falls to -0.01 and 0.01, respectively.

Consistent with the existing literature, this paper's results suggest that more mature firms are indeed less affected by changes in uncertainty – but not necessarily because of their size. At first, these findings seem at odds with results presented by Kim (2020), for example, who shows that larger firms – whether identified by their sales, assets, or number of business lines – tend to be less impacted by uncertainty than their smaller counterparts. However, the empirical approach applied by Kim (2020) does not control for firm age – making it difficult to determine whether age or size is truly insulating firms from the negative effects of uncertainty. We speculate that the association between uncertainty and firm performance is softened for more established firms since these companies may have comparatively larger business networks, longer-standing lending relationships, or greater managerial expertise, for example. These attributes – although difficult to assess and quantify – might play a significant role in allowing older firms to navigate periods of elevated uncertainty more successfully than less mature companies.

These same panel regressions are performed separately for Canadian and US samples (**Figures A4-A5**). This is done to explore whether different types of uncertainty impact Canadian and US firm performance distinctly. In general, panel regression results are found to be statistically insignificant when performed separately for Canada and the US. However, this subsample analysis still allows us to make two important inferences. Firstly, US uncertainty – whether proxied by US stock market volatility or policy uncertainty – is found to have as large an impact on Canadian firms' investment rates as Canadian uncertainty measures. This result is unsurprising given the comparative size of the US economy, the relative importance of export-oriented activities in Canada, and the historically high degree of integration between the two countries' economies. Secondly, and more surprisingly, Canadian EPU is found to have a larger and more statistically significant effect on US firms' TFP growth than on the TFP growth of Canadian firms. This would suggest that firms in the US are more strongly impacted by Canadian, rather than domestic policy uncertainty – which seems unlikely. However, it is unclear to what extent the Canadian EPU index is truly a barometer for economic policy uncertainty in Canadian media or simply a reflection of policy uncertainty originating from the US.

Finally, we use these empirical findings to better understand what role uncertainty played in driving the contraction in business activity observed during the COVID-19 pandemic. Consider that firms' investment rates, productivity growth, and Altman Z-scores experienced a weighted peak-to-trough decline of roughly 0.75, 0.70, and 0.11 standard deviations during the pandemic. Then, using parameter estimates from the previous panel regressions, we determine that – holding all else equal and assuming linearity in firms' responses[11] – a considerable portion of the pandemic-period decline in firm-level investment rates and Altman Z-scores, in particular, is attributable to uncertainty (**Table 11**). This analysis suggests that uncertainty played a prominent role in exacerbating the downturn in economic activity triggered by the outbreak of COVID-19. A similar conclusion is reached Baker et al. (2020b).

Table 11: Assessing the Contribution of Uncertainty to the COVID-19 Contraction

Uncertainty Measure		Investment Rate	Productivity Growth	Altman Z-Score
(1)	(2)	(3)	(4)	(5)
CAN RSMV	1.80	0.69	0.89	0.15
US RSMV	2.02	0.28	0.00	0.11
VIX	2.84	1.11	0.00	0.00
CAN EPU	1.85	0.23	0.02	0.10
US EPU	2.18	0.27	0.14	0.15
SRV	1.51	0.36	0.00	0.02

Note: Column (1) denotes the uncertainty measure of interest. Column (2) indicates the standard deviation increase in uncertainty observed between 2019Q4 and 2020Q2. Columns (3), (4), and (5) reflect the standard deviation decline in investment rates, productivity growth, and bankruptcy risk predicted by a one standard deviation increase in uncertainty, respectively.

5.2. Variance Decomposition

Variance decomposition is used to assesses how much each endogenously specified variable contributes to explaining variation within the SVAR system. For the purposes of this paper, variance decomposition specifically allows us to determine how much of the change in firm-level investment rates, productivity growth, and risk of bankruptcy is driven by uncertainty – rather than firm-level characteristics, monetary policy, or financial markets. This exercise is undertaken at forecast horizons between 1 and 20 quarters-ahead.

Figures 3-5 showcase forecast error variance decomposition for Canadian firms. We see that uncertainty explains only a small portion of total variation in firm-level performance. Investment rates, in particular, can broadly be described as deeply endogenous since they are predominantly explained by their own lags – rather than any other variables in the system. This differs notably from existing research, which finds that uncertainty explains a considerable portion of variation in Canadian aggregate investment (Moran et al., 2020). However, it is difficult to make direct empirical comparisons to macro-level research given that aggregate SVAR systems do not include firm-level characteristics – which have significant predictive power.

Next, we note the very prominent role that sales growth plays in driving productivity growth. This may, in part, explain why uncertainty was found to have a comparatively muted effect on firm-level TFP growth during the pandemic, as previously shown. Having said that, uncertainty – proxied by realized or implied stock market volatility – is still found to explain around 15 percent

[11] In this context, linearity describes a simplifying assumption made to more easily assess the impacts of uncertainty on pandemic-era firm performance. Specifically, we assume that firms' investment rates, productivity growth, and risk of bankruptcy change at a constant rate in response to a marginal increase in uncertainty.

of variation in productivity growth. These proxies are shown to explain around 10 percent of movements in firms' Altman Z-scores. As such, unlike Jurado et al. (2015), this paper does not find that macroeconomic uncertainty shocks explain more variation in economic activity than financial market volatility.

The same variance decomposition exercise is undertaken for US firms, as shown in **Figures 6-8**. Results are closely comparable. Again, uncertainty is found to explain only a relatively small proportion of total variation in firm-level outcomes. However, US firms' investment rates are not found to be as endogenous as their Canadian counterparts. That is, they are influenced to a much greater extent by other variables in the SVAR system, such as cash flow and Tobin's *q*. Uncertainty is found to explain up to 10 percent of variation in investment rates, which makes it a comparatively more important driver of firm-level investment in the US than in Canada.

As in Canada, TFP growth in the US is primarily driven by sales growth and comparatively more affected by uncertainty when proxied by financial market volatility. Unlike Canada, however, US bankruptcy risk is predominantly explained by stock market fluctuations and firms' investment opportunities, especially in the long-run. Curiously, we find that Canadian realized stock market volatility and economic policy uncertainty explain a greater proportion of US firms' bankruptcy risk than US financial market or economic policy uncertainty, respectively. This is consistent with results from the previously performed country-specific panel regressions, which showed than Canadian uncertainty proxies were associated with a larger decline in US firms' Altman Z-scores than a comparable increase in US uncertainty. As highlighted in the panel regression framework, stock return volatility has no strong bearing on firm-level bankruptcy risk in either country.

Figure 3: Variance Decomposition for Canadian Investment Rates

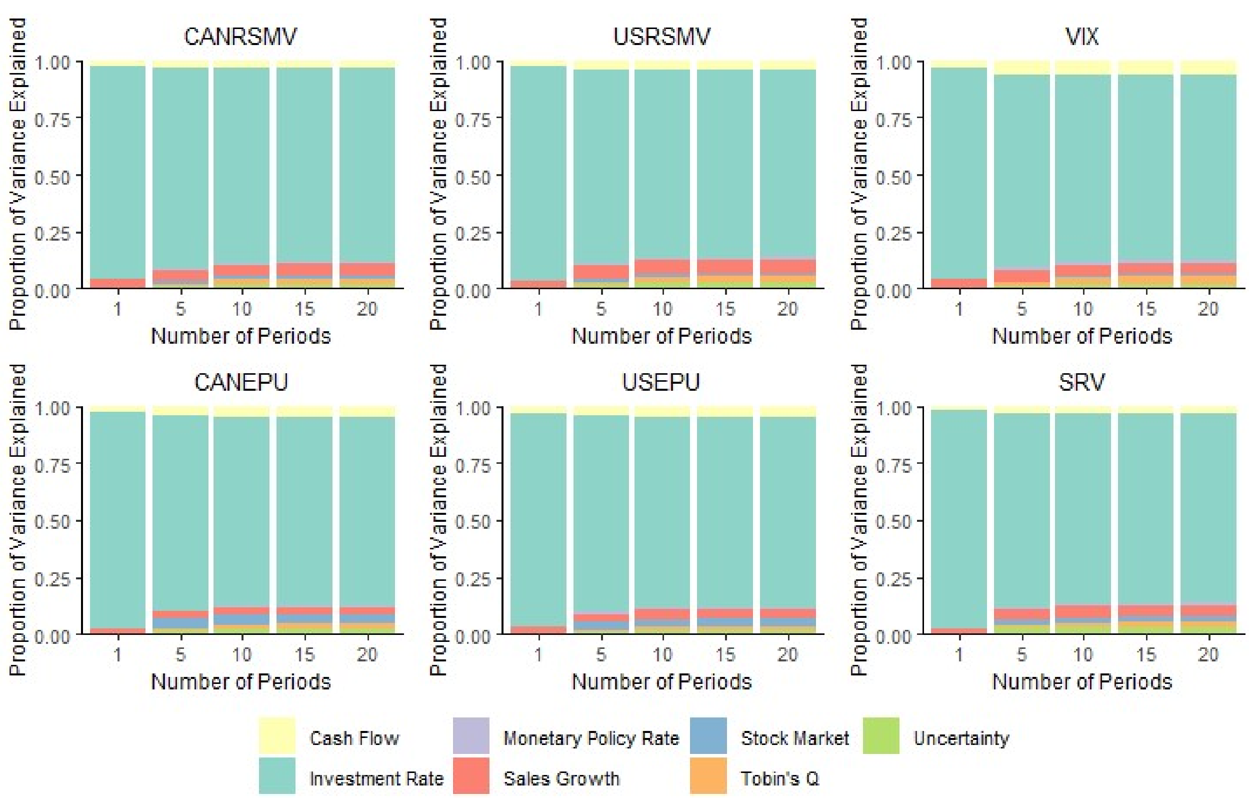


Figure 4: Variance Decomposition for Canadian Productivity Growth

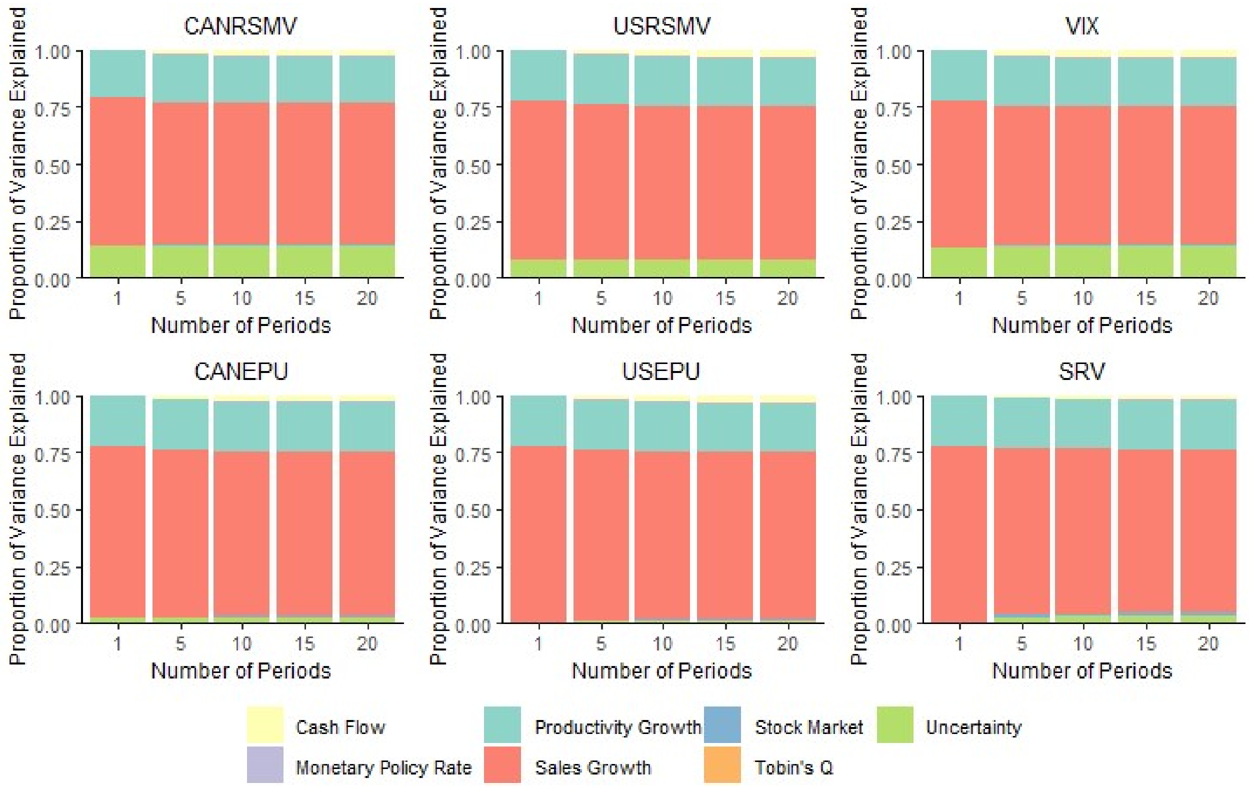


Figure 5: Variance Decomposition for Canadian Bankruptcy Risk

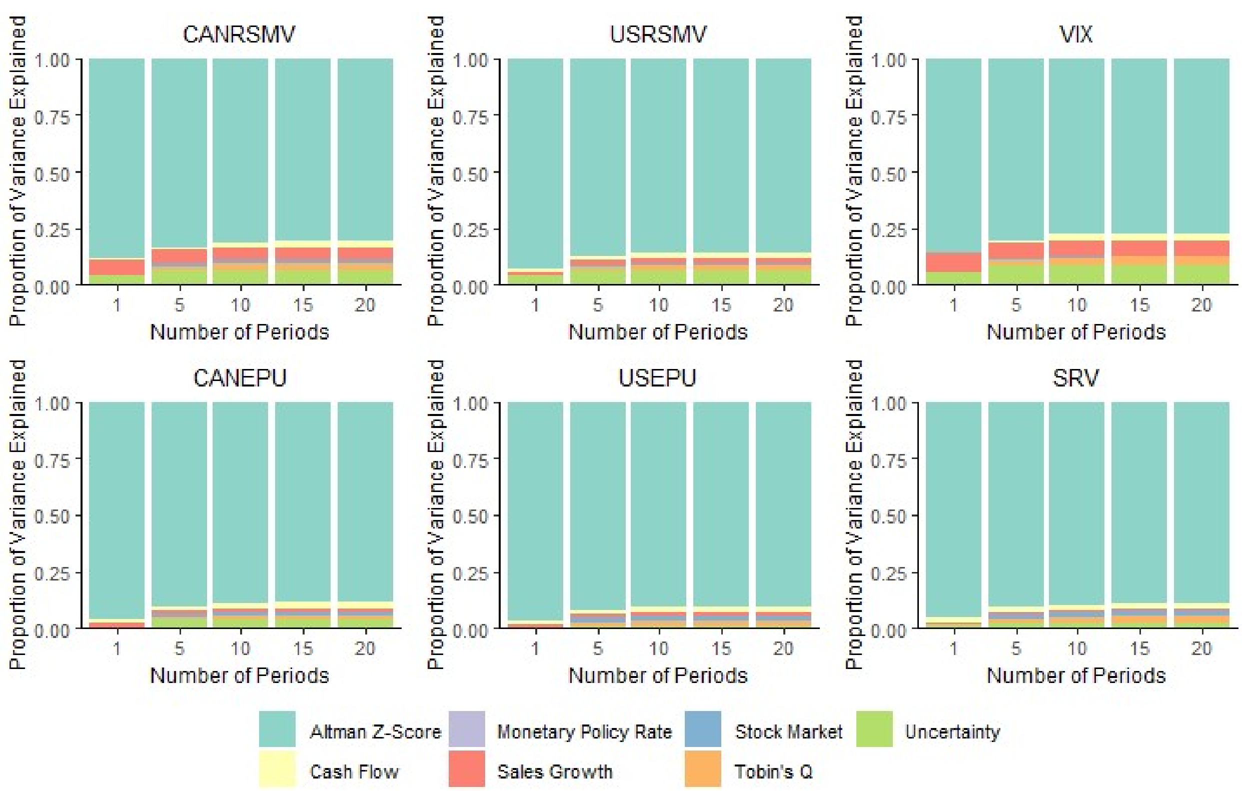


Figure 6: Variance Decomposition for US Investment Rates

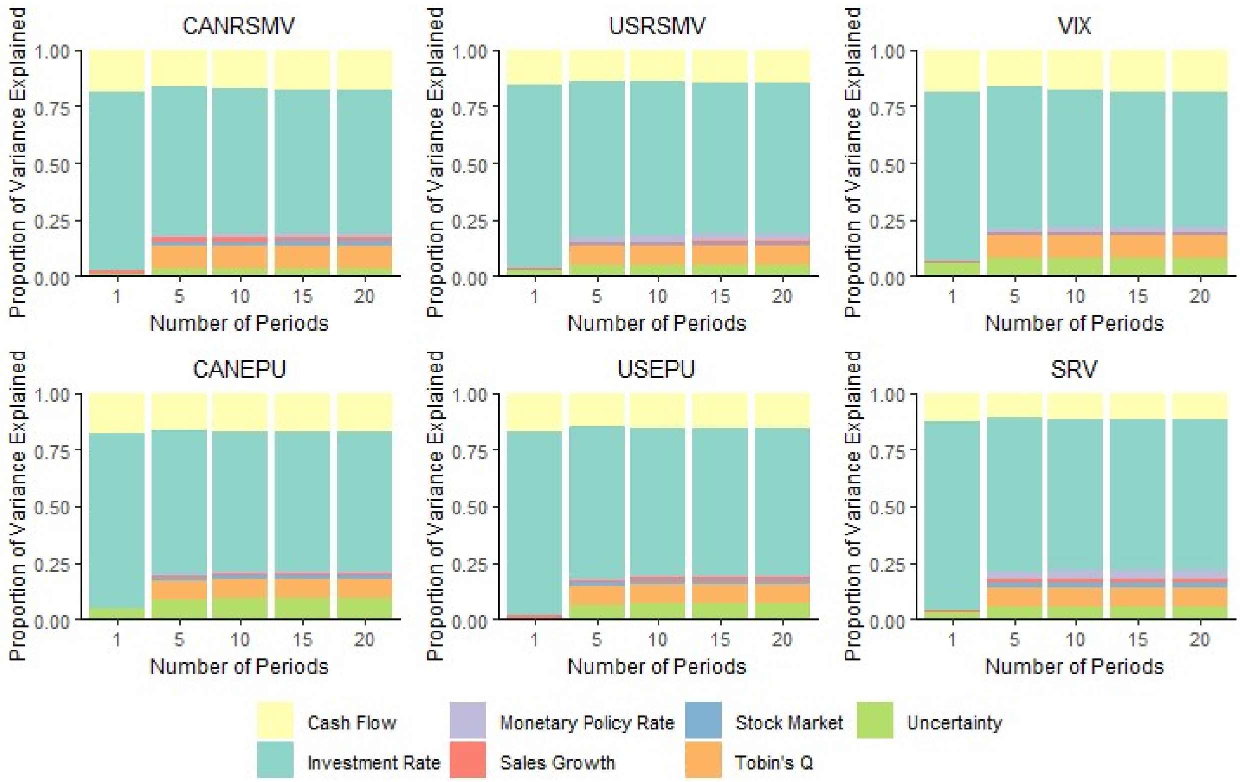


Figure 7: Variance Decomposition for US Productivity Growth

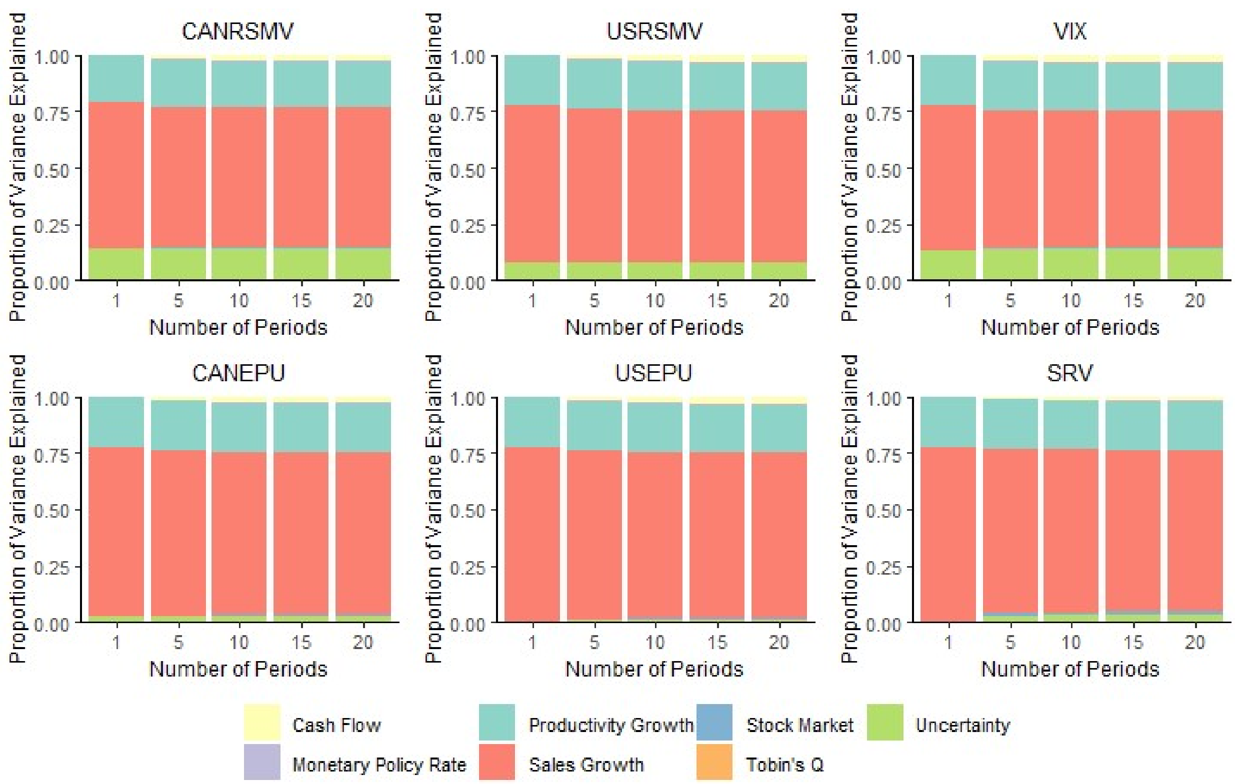
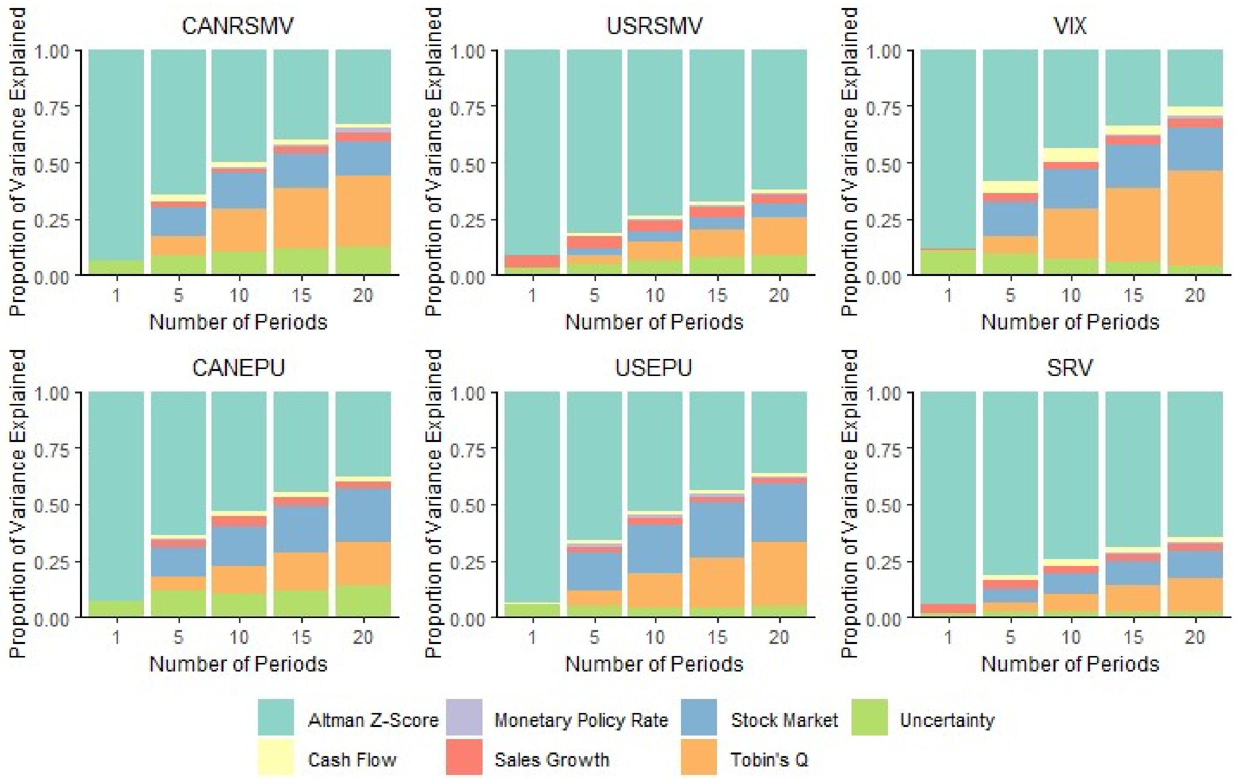


Figure 8: Variance Decomposition for US Bankruptcy Risk



5.3. Impulse Response Functions

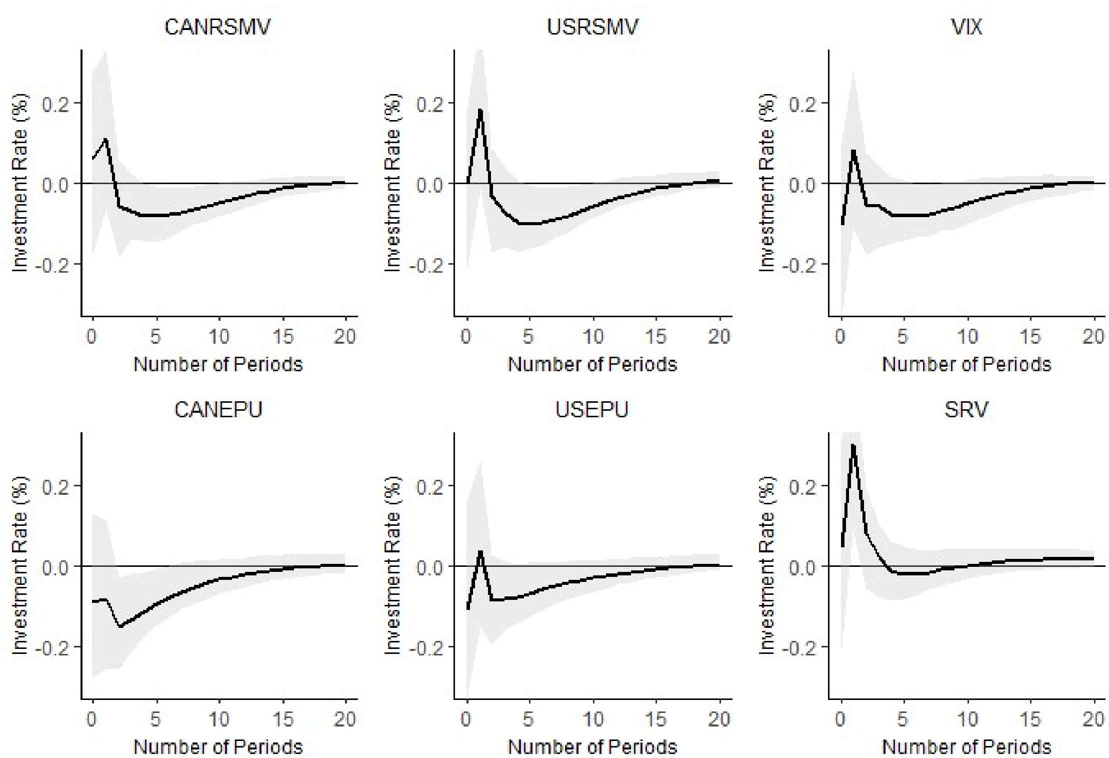
Figures 9-11 demonstrate how Canadian firm performance is affected by a one standard deviation uncertainty innovation. Investment rates are found to decline in the range of 0 to 0.15 percent immediately following the shock. This is significantly smaller than the 1.7 percent decrease in investment rates associated with a one standard deviation increase in uncertainty, as estimated in the previous panel regressions. Irrespective of which uncertainty proxy is used, investment rates are found to rebound substantially in the quarters following the shock. A full recovery is found to occur around 15 quarters after the innovation, in line with findings from the existing literature (Bloom, 2009; Gulen & Ion, 2016). US EPU innovations are found to have a similar effect on Canadian firm-level outcomes as a shock to Canadian EPU, supporting findings from Colombo (2013) which show that US EPU innovations have important cross-border effects. On the other hand, stock return volatility is hardly found to have any negative impact at all. This suggests that equity price fluctuations may not meaningfully limit the investment opportunities pursued by large, publicly-traded Canadian non-financial firms.

In several instances, investment rates are found to significantly surpass their pre-shock level before converging to their long-run equilibrium over the ensuing quarters. This phenomenon, known as overshooting, is well-documented in the existing literature and occurs as demand for investment – which builds up immediately following the shock, as predicted by real options theory – is rapidly unleashed (Bloom, 2009). Overshooting receives substantial attention because it is viewed as a costly feature of the economic adjustment process. That is, overshooting extends the period of economic disequilibrium and may invoke otherwise unneeded fiscal or monetary policy support. Interestingly, investment rates are only shown to surpass their long-run level when uncertainty is proxied by realized or implied stock market volatility. This finding is consistent with results put forward by Jurado et al. (2015), who shows that macroeconomic uncertainty innovations lead to sharp declines and protracted recoveries in firm performance but do not cause overshooting – unlike stock market volatility.

Productivity growth is found to decline more immediately and by a larger magnitude than investment rates. In some instances, firms' TFP growth falls by as much as 1.5 percent, which is particularly large given that Canadian firms in the sample have a weighted mean TFP growth rate of 2.7 percent. These declines are in line with those estimated in the previous panel regressions. The rebound in productivity growth is much sharper than the more protracted recovery observed for investment rates. In fact, the effects of the uncertainty innovation are now found to entirely wear off after just 5 quarters. Furthermore, we find little to no evidence of overshooting in this context. What is clear, however, is that stock market volatility is found to elicit a larger productivity growth response than a shock to economic policy uncertainty.

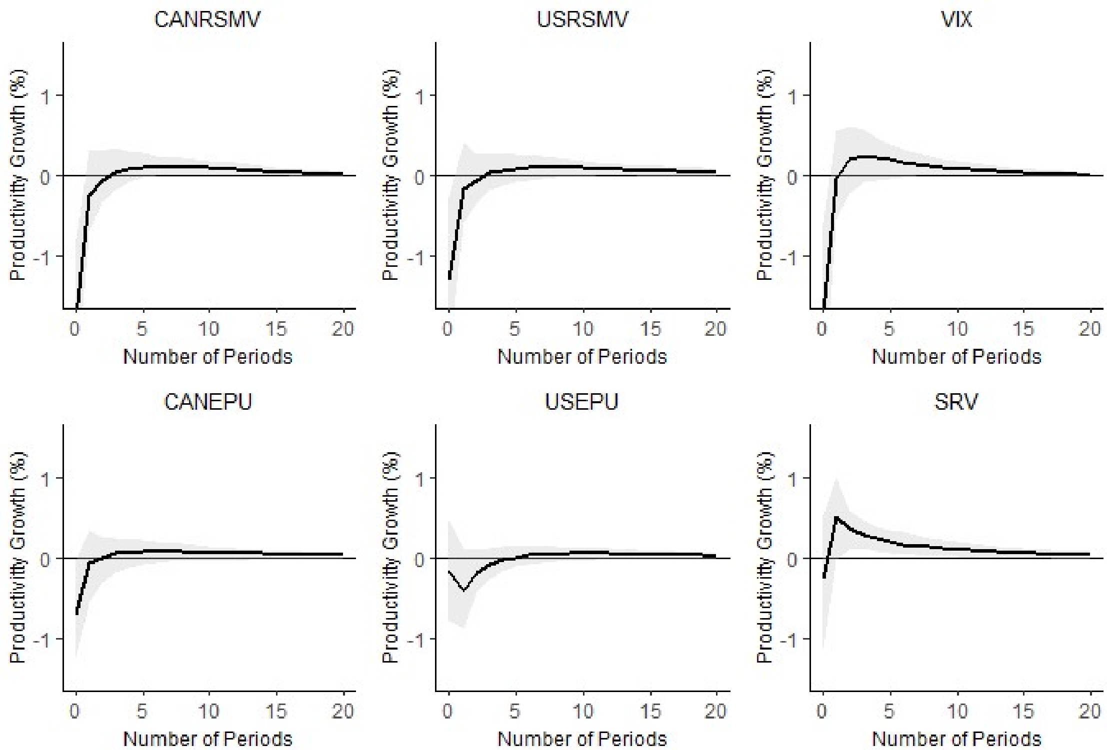
The impact of an uncertainty shock on bankruptcy risk is shown to be quite uniform. Namely, a one standard deviation uncertainty innovation reduces Altman Z-scores by around 0.05 points, irrespective of which proxy is used. This is notably smaller than the 0.28 point reduction in Altman Z-scores associated with a one standard deviation increase in uncertainty estimated within the fixed effects regression framework. In addition, the effects of the shock are found to dissipate after about 10 quarters. As was the case with investment rates, Canadian EPU is found to have a slightly larger negative impact than US EPU.

Figure 9: Impulse Response Functions for Canadian Investment Rates



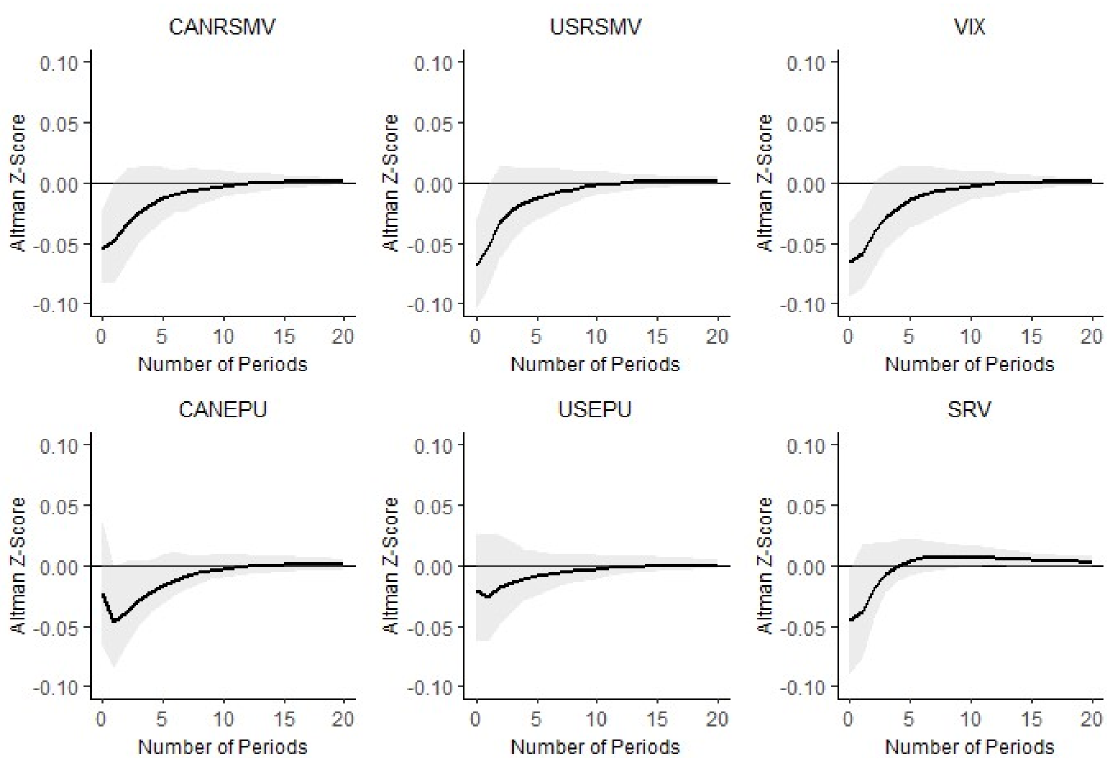
Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure 10: Impulse Response Functions for Canadian Productivity Growth



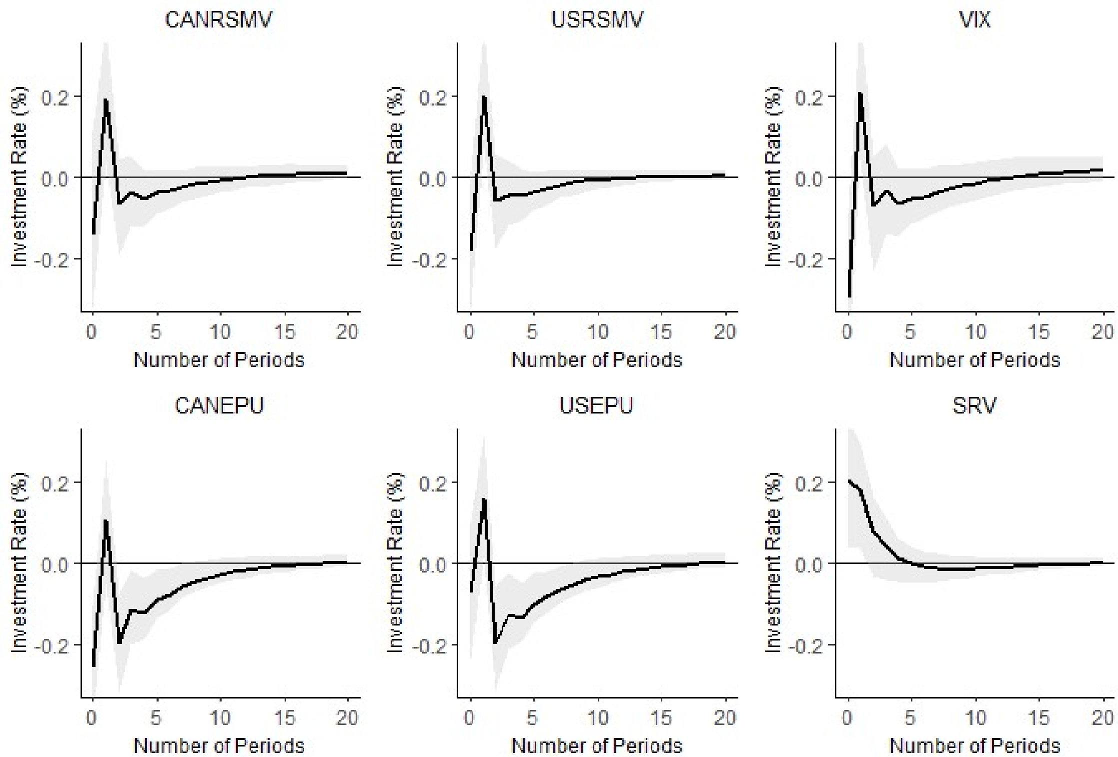
Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure 11: Impulse Response Functions for Canadian Bankruptcy Risk



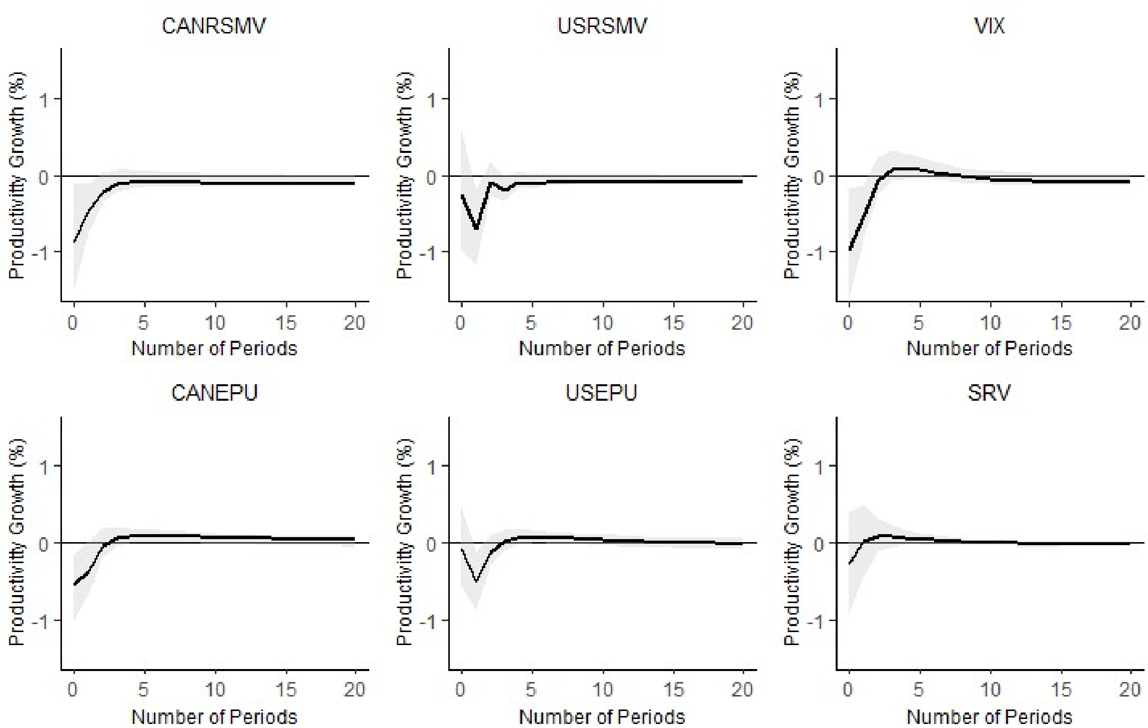
Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure 12: Impulse Response Functions for US Investment Rates



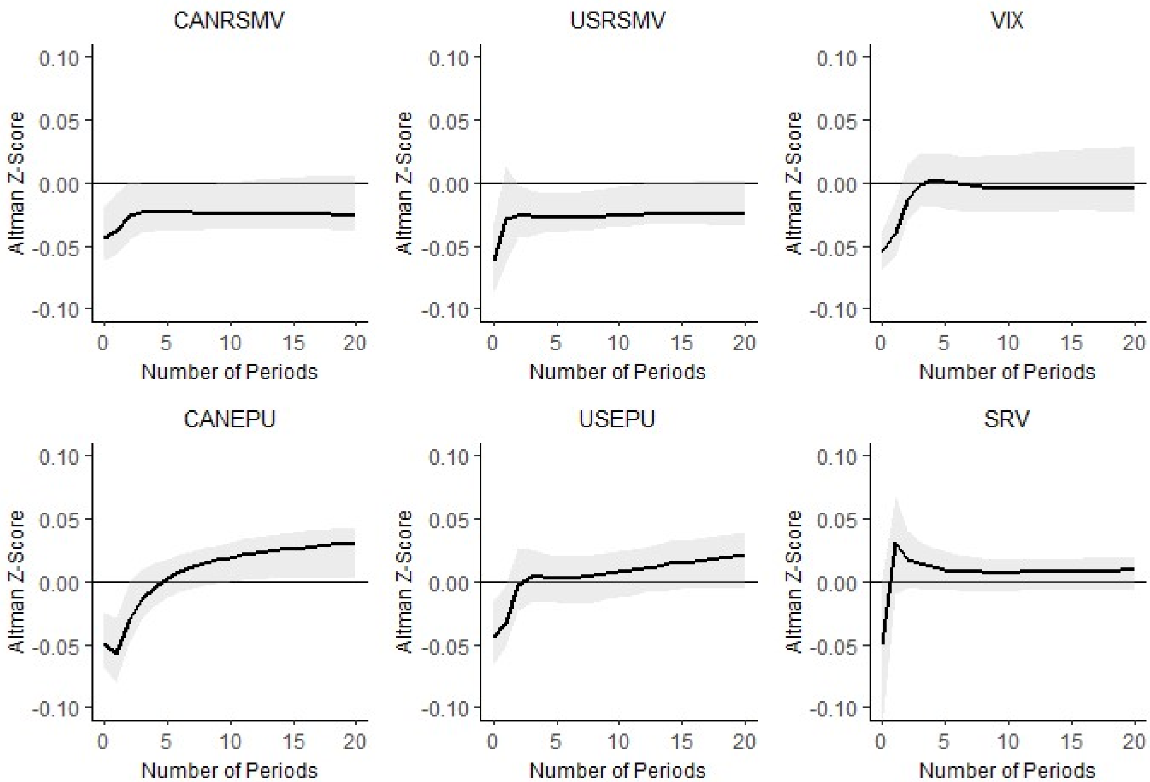
Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure 13: Impulse Response Functions for US Productivity Growth



Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure 14: Impulse Response Functions for US Bankruptcy Risk



Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figures 12-14 illustrate the relationship between uncertainty innovations and the conditional expectations of measures of firm performance for US firms. By orders of magnitude, the decline in US investment rates is found to be approximately the same as in Canada. However, we note that realized stock market volatility is found to have a larger short-run impact on American firms, given that investment rates decline by as much as 0.20 percent immediately following the shock. This is not so dissimilar to the decline in investment rates associated with a one standard deviation increase in uncertainty, estimated with panel regressions. The same rebound and overshoot is observed again, and actually seems to be more significant for the US subsample.

The link between US firm-level TFP growth and uncertainty is generally found to be more muted than for Canadian firms. Specifically, uncertainty innovations are not found to reduce firm-level TFP growth by more than 1 percent in any instance. In addition, we again see that financial market volatility has a larger effect on TFP growth than policy uncertainty. Like for Canadian firms, a one standard deviation shock to uncertainty is always found to reduce Altman Z-scores by around 0.05 initially. However, we note that a full recovery in Altman Z-scores is not observed over the 20-quarter horizon when the innovation is applied to Canadian or US realized stock market volatility. This suggests that shocks to stock return volatility have particularly long-term consequences for firms' liquidity and reflects the importance of equity to the capital structure of the large publicly traded firms studied in this paper. As was the case for Canadian firms, overshooting is not found to be a prominent feature of the disequilibrium adjustment process for US TFP growth and bankruptcy risk.

5.4. VAR Model Diagnostics

Irrespective of which uncertainty proxy or firm performance measure is specified in the SVAR framework, all of the models' equations are shown to record moderately high F-statistics and R^2 values, suggesting good model fit. Results from Granger causality tests indicate that uncertainty measures generally do not Granger cause firm outcomes (**Table 12**). This result holds for both Canadian and US subsamples, as well as across the three firm performance measures. Results from CUSUM stability tests suggest that the SVAR models are stationary. However, statistically significant ARCH LM test results indicate that many of the estimated models suffer from autocorrelation (**Table 13)**. That is, residuals are found to be dependent on their past values, which suggests that there remains useful content in the time series that has yet to be exploited in modeling. This is largely a consequence of having estimated relatively low-order models.

Table 12: Granger Causality Results

	Canada			US		
	Investment Rate	Productivity Growth	Bankruptcy Risk	Investment Rate	Productivity Growth	Bankruptcy Risk
CAN RSMV	1.00	0.16	0.04	0.01	0.04	2.04
US RSMV	1.91	0.08	0.00	0.08	0.56	1.80
VIX	2.59*	0.51	0.01	1.47	0.67	9.97***
CAN EPU	1.91	0.00	1.06	0.00	0.91	2.63*
US EPU	0.02	1.37	0.00	0.02	1.67	1.26
SRV	2.97*	2.81*	0.27	4.89**	0.30	2.00

Note: Figures displayed in table are *F*-statistics from Granger causality tests. ***, **, * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Table 13: ARCH LM Autocorrelation Test Results

	Canada			US		
	Investment Rate	Productivity Growth	Bankruptcy Risk	Investment Rate	Productivity Growth	Bankruptcy Risk
CAN RSMV	1076.7***	1081.3***	1183.8***	1324.8***	1251.7***	1197.2***
US RSMV	1021.0***	1024.5***	1055.2***	1574.9***	1538.3***	1639.0***
VIX	1011.9***	1042.7***	1119.8***	1243.0***	1186.8***	1100.1***
CAN EPU	916.5***	1003.0***	991.32***	1007.4***	1029.8***	1084.5***
US EPU	956.4***	1039.3***	1025.5***	1199.1***	1163.0***	1113.9***
SRV	962.3***	1086.2***	992.97***	1484.2***	1448.8***	1653.1***

Note: Figures displayed in table are Chi-squared statistics from ARCH LM tests. ***, **, * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Increasing the lag order to at least 6 – which is higher than suggested by conventional information criteria – is found to resolve autocorrelation concerns, but at the cost of increasing model complexity. When doing so, we note that the models' IRFs become substantially less smooth while the proportion of variance explained by uncertainty is found to rise. Increasing the models' lag length is also found to produce more statistically significant Granger causality results.

Exploratory analysis suggests that the estimated SVAR models are somewhat sensitive to variable ordering. Although impulse responses change quantitatively when the variable ordering is altered, the same qualitative results generally still hold. That is, we still observe a significant deterioration in investment rates, productivity growth, and Altman Z-scores. When uncertainty is placed last in the SVAR's recursive ordering – that is, uncertainty is assumed to respond contemporaneously to other variables in the system without affecting them – then firm performance is no longer found to decline in response to an uncertainty shock. However, this extreme recursive ordering is not thought to be particularly realistic or empirically supported.

GIRFs are used with the aim of approaching structural analysis more agnostically and further assessing robustness of the results (Pesaran & Shin, 1998). Results, displayed in **Figures A6-A11** indicate that uncertainty shocks generally have a negative impact on firm performance irrespective of how variables in the system are ordered. In particular, uncertainty innovations are still found to decrease firm-level investment rates, but not nearly as significantly as when the shock is assumed to be orthogonal, and not at all when uncertainty is proxied by stock market volatility. Productivity growth is still shown to fall immediately after an uncertainty shock – but only by up to 0.20 percent, rather than 1.5 percent. In addition, Altman Z-scores are not always found to decrease in response to an uncertainty innovation, especially for US firms. This calls into question the previously identified relationship between uncertainty and bankruptcy risk.

6. Conclusion

6.1. Discussion of Results

The primary objective of this paper is to assess the extent to which uncertainty impacts firm performance for publicly traded, non-financial companies in Canada and the US. Specifically, it employs panel regression and vector autoregression models to determine how, to what extent, and for how long measures of economy-wide and firm-specific uncertainty affect firms' investment rates, total factor productivity growth, and risk of bankruptcy.

This paper finds that uncertainty is negatively associated with firm performance. Panel regressions reveal that, on average, a one standard deviation increase in uncertainty is associated with a 1.7 percent, 1.1 percent, and 0.28 point decline in quarterly investment rates, productivity growth, and Altman Z-scores, respectively. In addition, we show that the effects of uncertainty are notably heterogenous across firm age. That is, uncertainty is shown to negatively impact less mature firms more than older companies. A structural analysis of SVAR models indicates that uncertainty innovations lead to a rapid deterioration, rebound, and – in some cases – overshoot in firm performance. Forecast variance decomposition indicates that uncertainty is not the primary driver of firm-level outcomes while IRFs suggest that the decline in firm performance caused by uncertainty is not as large as suggested by fixed effects modelling. We find that investment rates, productivity growth, and Altman Z-scores fall by around 0.10 percentage points, 1 percentage point, and 0.05 points, respectively, in the quarter following an uncertainty innovation. In general, stock market volatility is shown to negatively affect firm performance by more than policy uncertainty, and is more often associated with overshooting. Results in this paper are in line with those put forward in the existing literature. However, we note that both fixed effect parameter estimates and findings from structural analysis are not always statistically significant, especially when Canadian and US subsamples are studied separately.

6.2. Potential Policy Implications

Policymakers can play a crucial role in reducing the degree of perceived uncertainty – or at least, how much they contribute to its fluctuation. That is, more can be done to ensure that relevant economic and regulatory policies are transparently and unambiguously communicated. To a large extent, these best practices are already implemented by central banks, which make clearly discussing current and future policy objectives a priority – in large part because of how impactful forward guidance can be as a monetary policy tool. In addition, policymakers could aim to provide greater support to firms during recessionary periods characterized by high uncertainty, such as during the Global Financial Crisis and COVID-19 pandemic. In fact, it may even be advisable for policymakers to more closely monitor uncertainty proxies in order to ensure that additional stimulus is provided as the degree of uncertainty rises and withdrawn as uncertainty dissipates. Designing policy in this way may help to soften economic contractions and accelerate economic recovery, all while avoiding costly overshooting in the disequilibrium adjustment process.

6.3. Opportunities for Future Research

Future researchers may contribute to the existing literature in a number of ways. For instance, it would be interesting to investigate to what extent the economic impacts of uncertainty are heterogenous across industries. It is conceivable that firms in industries exposed to additional sources of uncertainty – such as exchange rate risk or commodity price volatility – may experience worse outcomes following a shock to economic policy uncertainty. This may include firms in retail and wholesale trade or mining, for example. Consistent with real options theory, firms in industries where investment projects are more likely to be irreversible or have long lead times – such as construction, mining, or manufacturing – may also be disproportionately affected by uncertainty shocks since employing a “wait and see” approach in these cases would severely impact a company’s current and future competitiveness. Finally, researchers may choose to explore whether firms operating in regulation-sensitive subsectors, such as pipeline construction or pharmaceutical preparations, for example, are comparatively more affected by policy uncertainty than financial market volatility. This analysis would help to better understand how different kinds of uncertainty impact businesses differently, and how significant a role policymakers may be able to play in reducing the adverse effects of uncertainty on firm activity.

Given that Canadian firms represent only a small portion of total observations in the Compustat database, researchers concerned with studying Canadian firm performance may consider using other panel datasets. These may include large, micro-level business datasets maintained by Statistics Canada or Dun & Bradstreet, for example. Doing so would also allow for the impacts of uncertainty on the economic activities of private firms, rather than only publicly listed firms, to be closely examined. This approach would allow for a better representation of the Canadian economy, and would consequently make results more externally valid and thus policy-relevant.

Finally, researchers may also choose to explore similar empirical questions with a more nuanced econometric approach. For instance, the use of non-linear VAR models may be well motivated given that firms have been shown to typically operate near their hiring and investment thresholds (Bloom, 2009). Above this point, firms engage in hiring and investing while below this point, they take no action. If these asymmetric effects are meaningful, then a small increase in uncertainty would be expected to elicit a meaningful firm-level response while a decrease in uncertainty would instead have little to no effect on firm outcomes. In this case, the use of standard VAR models – rather than threshold VAR (TVAR) models, for example – may act to misestimate the true negative effects of uncertainty shocks.

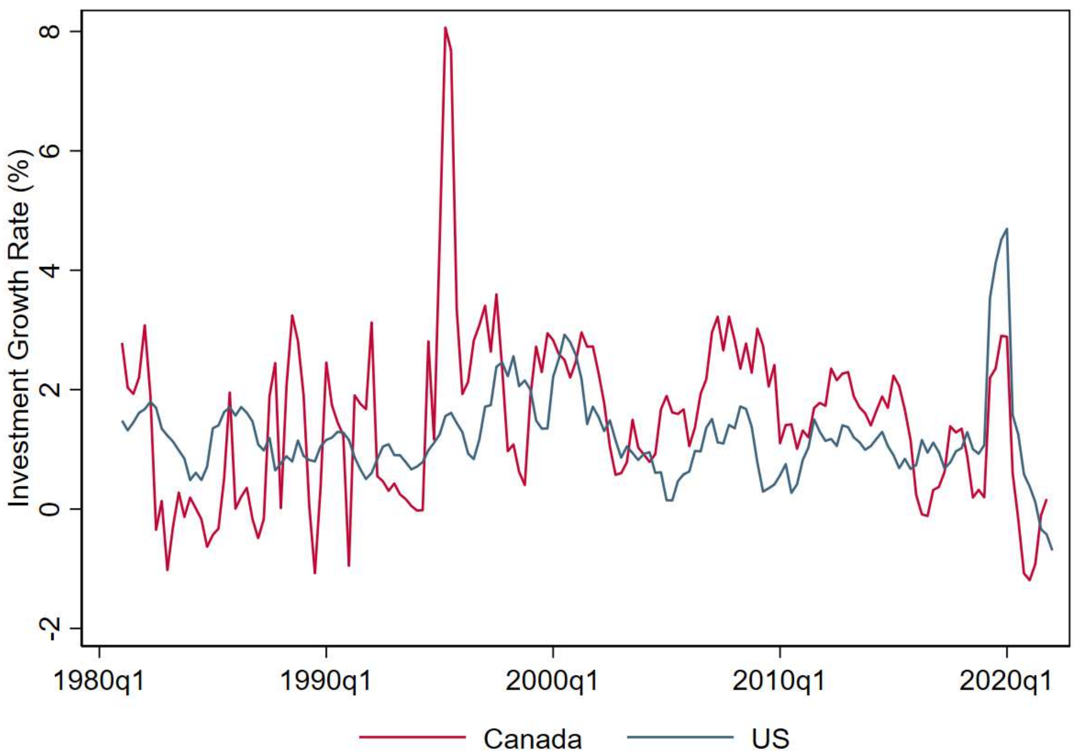
7. Appendix

Table A1: Productivity Measures

Variable	Olley-Pakes (1996)	OLS	Fixed Effects
$log(Capital)$	0.329***	0.312***	0.234***
	(0.015)	(0.001)	(0.001)
$log(Labour)$	0.663***	0.656***	0.624***
	(0.005)	(0.001)	(0.001)
Productivity	0.430	1.369	1.086
Productivity Growth	0.028	0.027	0.025
n	493,362	502,654	502,654

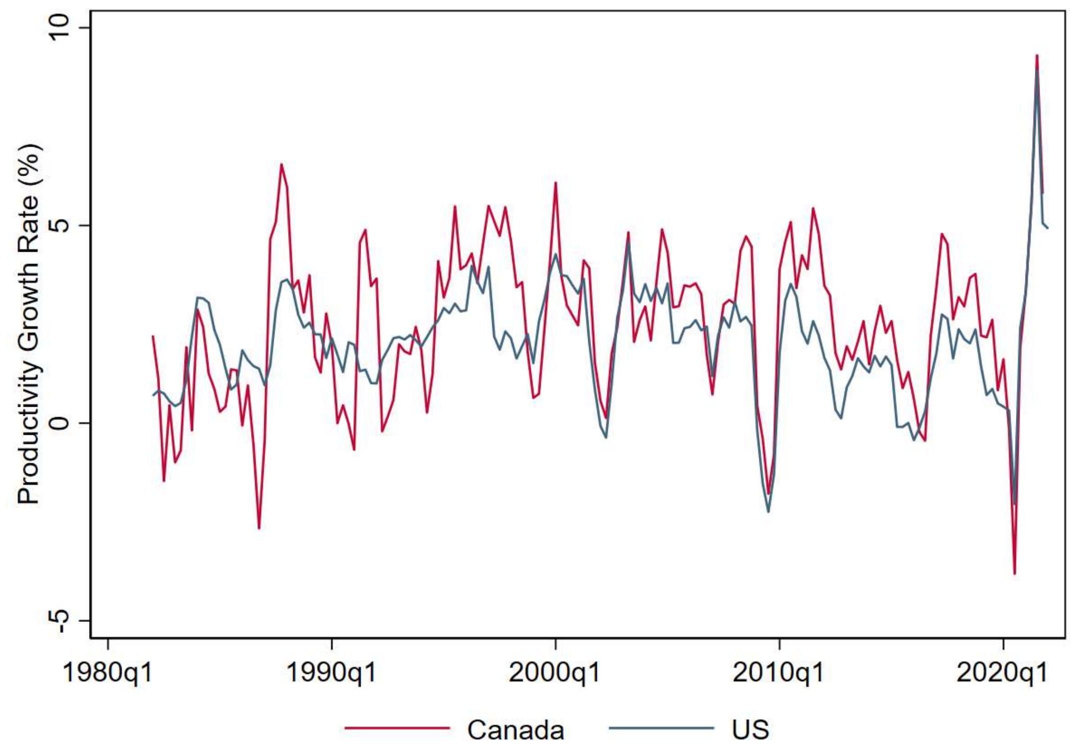
Note: The dependent variable in each specification is the natural log of real total revenue. Investment is used as a proxy for unobserved productivity shocks in the Olley-Pakes (1996) model. All specifications control for firm age. The fixed effects model includes firm fixed effects. Productivity is the unweighted sample-wide median of firm-specific productivity. Standard errors are bootstrapped using 50 replications when estimating the Olley-Pakes (1996) model. Robust standard errors are shown in parentheses. ***, **, * denote statistical significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

Figure A1: Investment Rate by Country



Note: Investment rate is expressed as a 4-quarter moving average and weighted by firms' average total assets.

Figure A2: Productivity Growth by Country



Note: Productivity growth is expressed as a 4-quarter moving average and weighted by firms' average total assets.

Figure A3: Risk of Bankruptcy by Country

Note: Altman Z-scores are expressed as a 4-quarter moving average and weighted by firms' average total assets. Bankruptcy risk is winsorized as it is found to be especially variable in the 1980Q1-1999Q4 period.

Table A2: Sectoral Distribution of Firms

Sector	Canada	US
Agriculture, Forestry, and Fishing	101 (0.28%)	1,276 (0.39%)
Construction	293 (0.81%)	4,380 (1.33%)
Manufacturing	11,224 (31.16%)	163,114 (49.41%)
Mining	14,204 (39.44%)	16,558 (5.02%)
Retail Trade	1,579 (4.38%)	24,189 (7.33%)
Services	3,486 (9.68%)	48,232 (14.61%)
Transportation and Utilities	3,926 (10.90%)	58,827 (17.82%)
Wholesale Trade	1,204 (3.34%)	13,552 (4.11%)

Note: Industries are defined using standard industrial classification codes (SIC). Firms in the Finance, Insurance, and Real Estate as well as Public Administration sectors are removed as part of data-cleaning process.

Table A3: Correlation Matrix

Variable	Investment Rate	Productivity Growth	Altman Z-Score	CAN RSMV	US RSMV	VIX	CAN EPU	US EPU	SRV
				Panel A: Canada					
Investment Rate	1.00								
Productivity Growth	-0.01	1.00							
Altman Z-Score	0.12	-0.01	1.00						
CAN RSMV	-0.01	-0.04	-0.02	1.00					
US RSMV	-0.02	-0.04	-0.03	0.93	1.00				
VIX	-0.02	-0.03	-0.03	0.88	0.95	1.00			
CAN EPU	-0.01	-0.10	-0.04	-0.02	0.11	0.18	1.00		
US EPU	-0.03	-0.05	-0.04	0.29	0.39	0.51	0.71	1.00	
SRV	-0.04	-0.04	-0.08	0.49	0.51	0.61	-0.05	0.22	1.00
				Panel B: US					
Investment Rate	1.00								
Productivity Growth	-0.03	1.00							
Altman Z-Score	0.10	-0.02	1.00						
CAN RSMV	-0.03	-0.03	-0.02	1.00					
US RSMV	-0.03	-0.03	-0.03	0.89	1.00				
VIX	-0.03	-0.02	-0.03	0.81	0.95	1.00			
CAN EPU	-0.01	-0.02	-0.01	0.01	0.06	0.13	1.00		
US EPU	-0.02	-0.01	-0.02	0.27	0.27	0.41	0.72	1.00	
SRV	-0.02	-0.01	-0.02	0.45	0.45	0.56	-0.19	0.02	1.00

Figure A4: Impact of Uncertainty on Firm-Level Performance in Canada

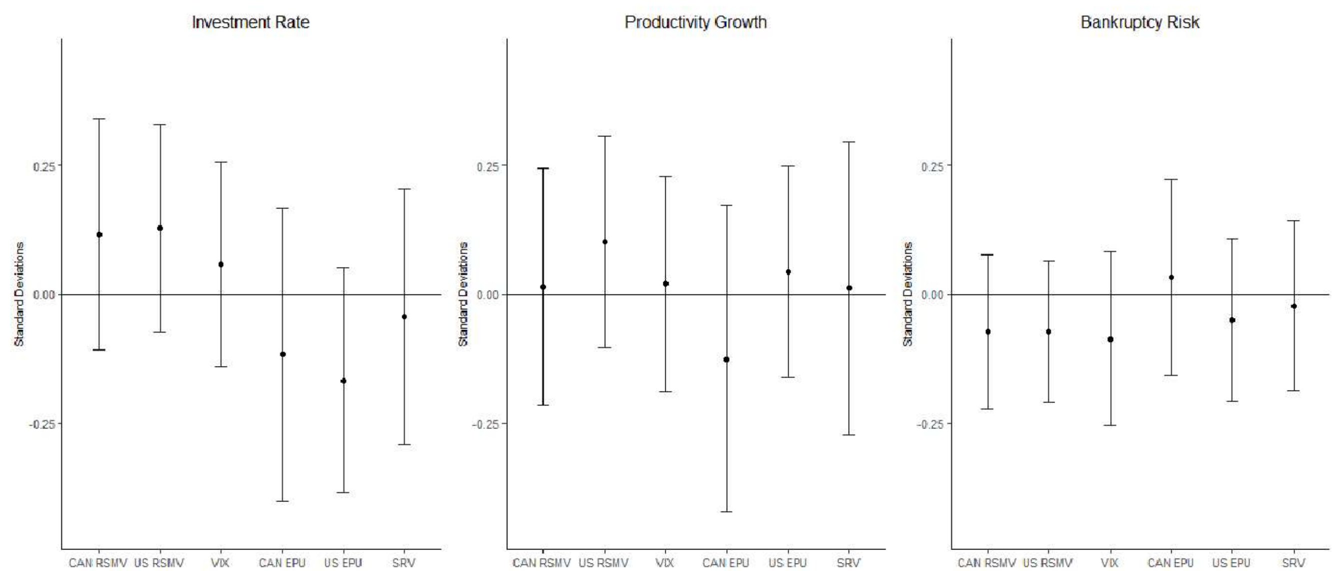
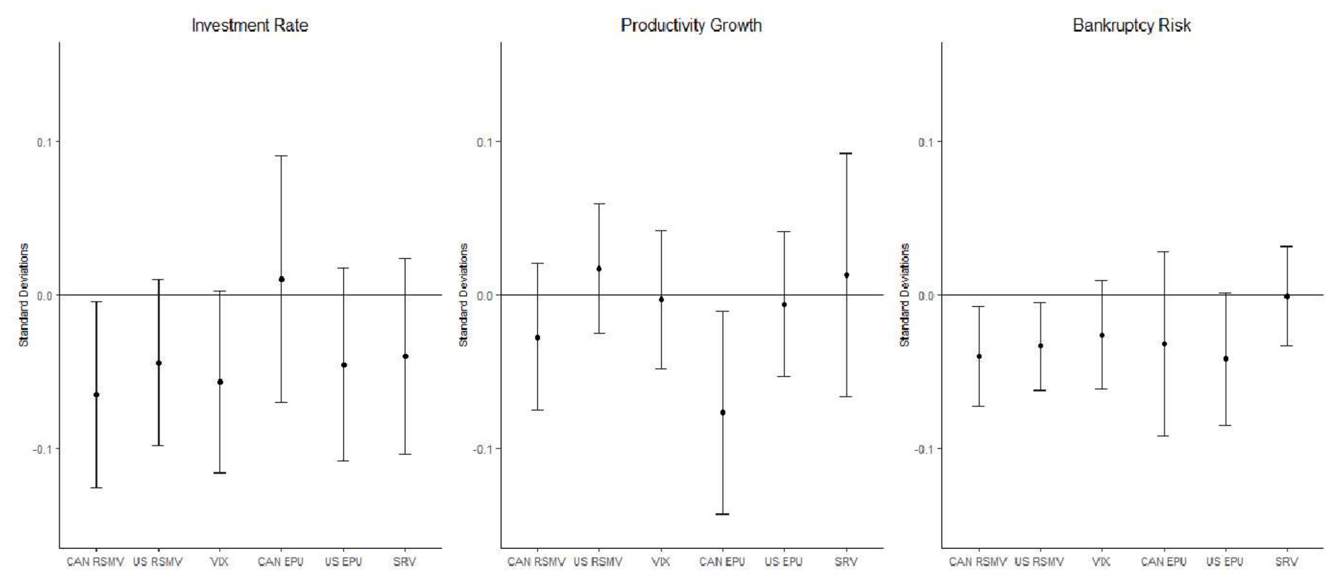
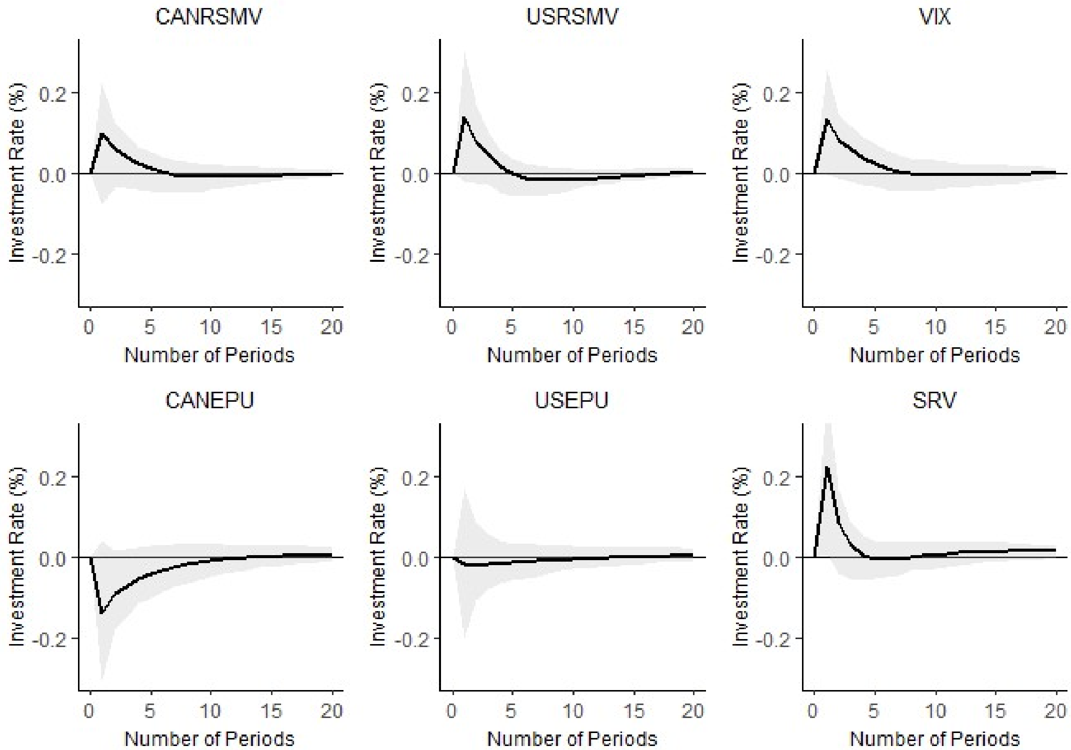


Figure A5: Impact of Uncertainty on Firm-Level Performance in US



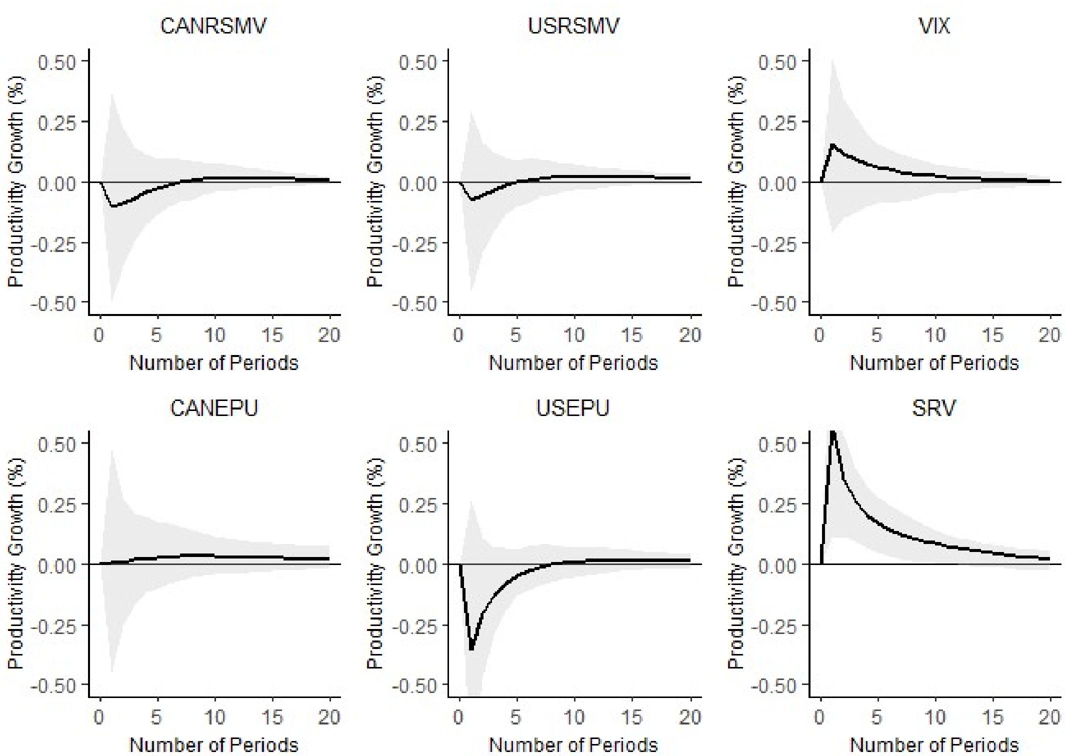
Note: Plots display β_1 coefficient from augmented panel regressions specified in (10). $Date \times Country$ fixed effects are replaced with $Date$ fixed effects. Confidence intervals display 95 confidence bands.

Figure A6: Generalized Impulse Response Functions for Canadian Investment Rates



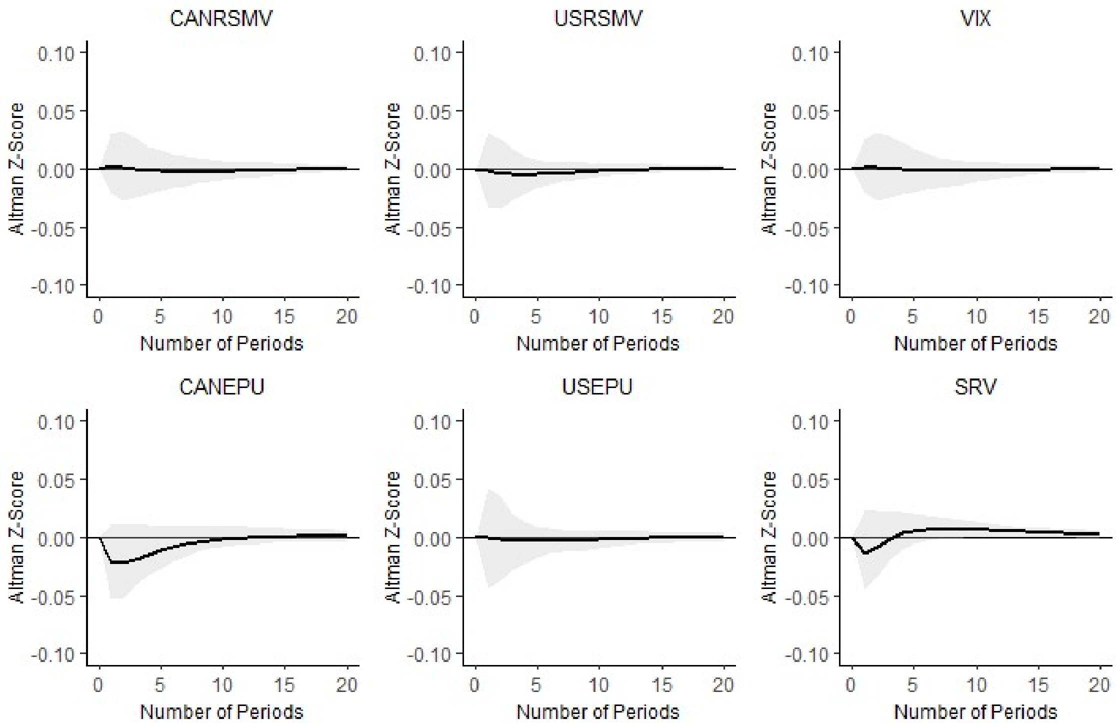
Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure A7: Generalized Impulse Response Functions for Canadian Productivity Growth



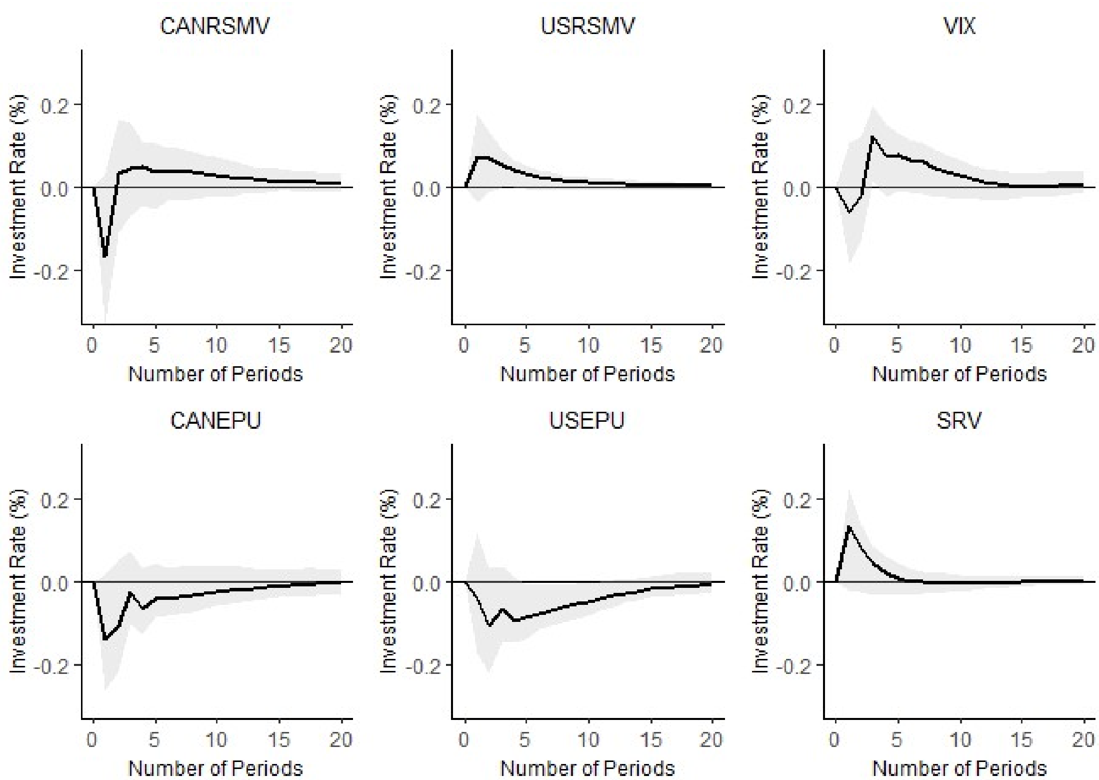
Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure A8: Generalized Impulse Response Functions for Canadian Bankruptcy Risk



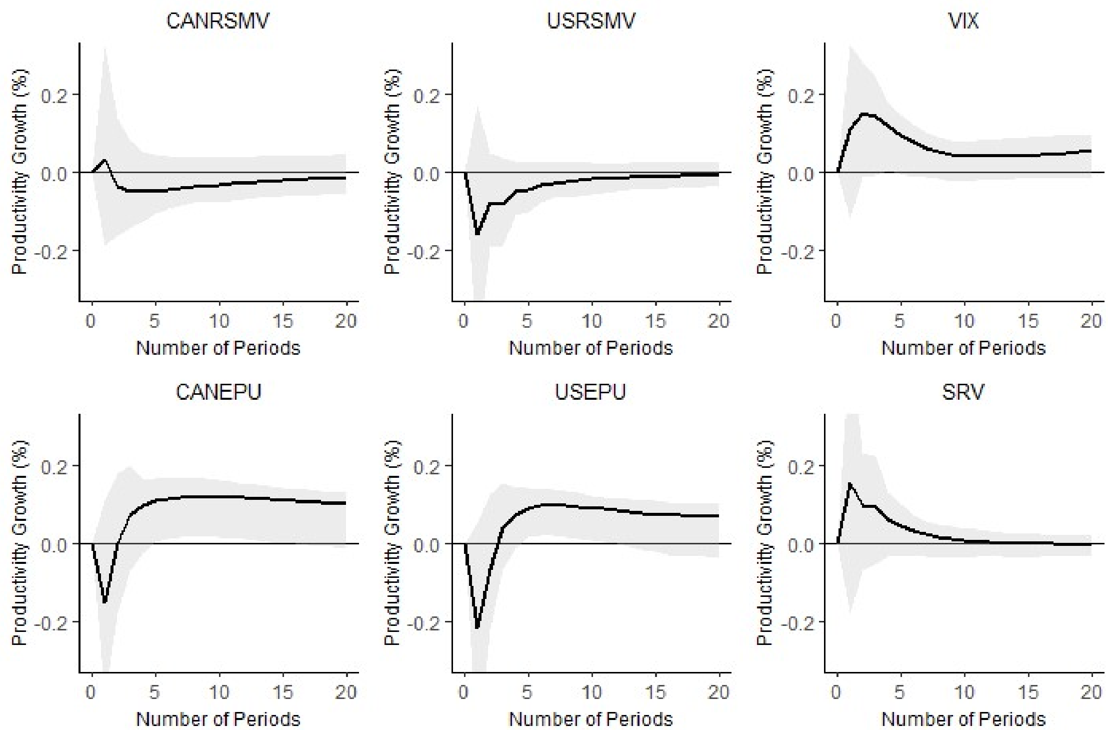
Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure A9: Generalized Impulse Response Functions for US Investment Rates



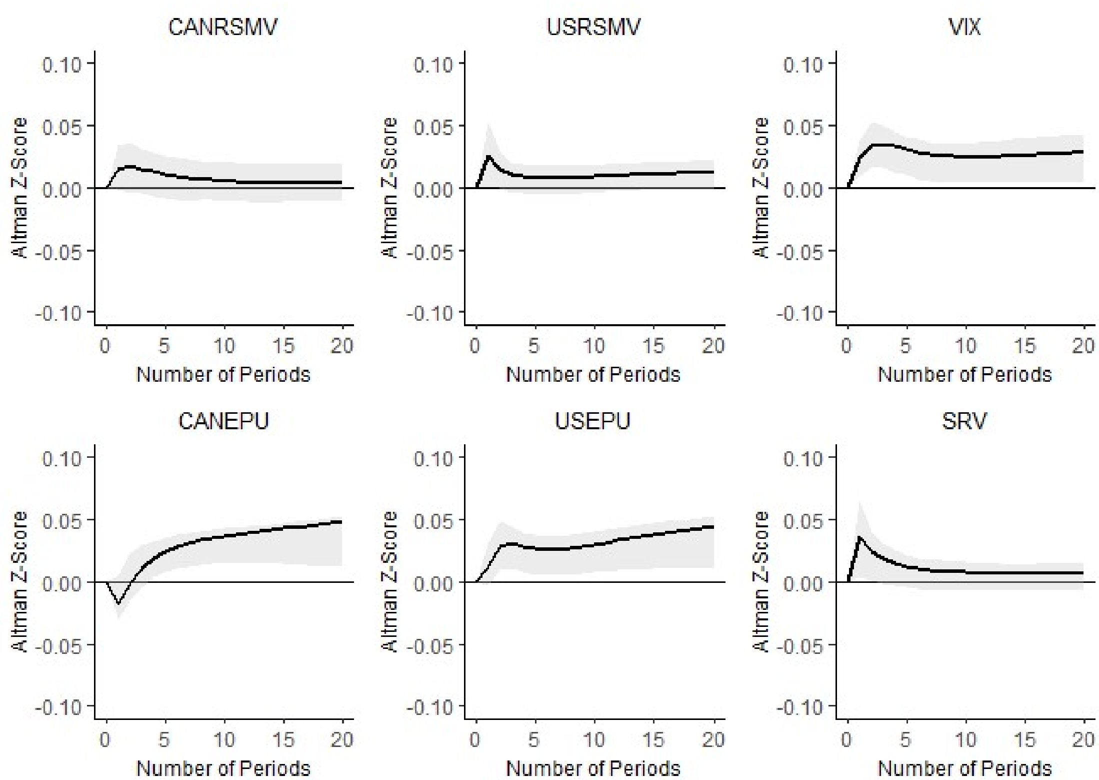
Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure A10: Generalized Impulse Response Functions for US Productivity Growth



Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

Figure A11: Generalized Impulse Response Functions for US Bankruptcy Risk



Note: Shaded regions represent 90 percent confidence intervals, bootstrapped with 250 runs.

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