The Impact of Economic Uncertainty on Housing, Labor and Financial Markets

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CHAPTER 1

Introduction

This dissertation comprises five chapters on economic uncertainty[1]. Chapter 1 provides a brief overview of the literature and the motivation for this dissertation. Moreover, the chapter also introduces the concept of uncertainty and presents different measures of uncertainty. Chapter 2 examines the role of economic uncertainty in explaining the U.S. Initial Public Offering (IPO) issue cycles, while chapter 3 analyzes the impact of uncertainty on the U.S. housing market. Chapter 4 quantifies the effects of uncertainty on (disaggregated) import flows using German data and is accompanied by an analysis on the revealed comparative advantage in trade of the EU-27 countries. Chapter 5 concludes.

The first section of this chapter provides an overview of the research on uncertainty and explains the motivation behind the dissertation, while the section 1.2 introduces the notion of uncertainty and presents various proxies for economic uncertainty which are used frequently in the dissertation. Section 1.3 presents descriptive statistics and causality tests of the uncertainty measures.

[1] In this dissertation, the terms “economic uncertainty" and “uncertainty" are used interchangeably.

1.1 Overview and Motivation

"Uncertainty is largely behind the dramatic collapse in demand. Given the uncertainty, why build a new plant, or introduce a new product? Better to pause until the smoke clears."
Oliver Blanchard[2](*The Economist*, January 29, 2009, p. 84.)

In recent years, research on economic uncertainty as a factor influencing decisions of economic agents has enjoyed increased popularity, reflecting the recent growth of this strand of literature following the financial crisis. There are two main factors behind this boost in interest in uncertainty. First, the policy attention on the topic has increased due to the fact that uncertainty was likely a major driver of the Great Recession. Second, the increased availability of empirical proxies for uncertainty has facilitated empirical investigations.

Two main transmission mechanisms through which uncertainty might affect real economic activities have been discussed intensely. Real options effect arises in periods with high uncertainty under the assumption of (partial) irreversibility of investments (e.g., Bernanke, 1983; McDonald and Siegel, 1986; Pindyck, 1991; Bloom, 2009). The authors argue that firms look at their investment choices as a series of option and emphasize the importance of waiting: in periods of high uncertainty, firms wait and gather more information before making an irreversible investment decision. For example, if a firm is uncertain about the future demand for its products it may not want to invest in a new plant to increase production capacity, but prefers to wait and postpone the investment to future periods when uncertainty dissolves. This real options effect relies on firms possessing the ability to wait and irreversible (or at least costly to reverse) investment decisions; if the investment can be easily reverted without substantial costs or the firms immediately want to launch a new product, the option to wait may not be valuable.

Moreover, models combining uncertainty shocks with some sort of financial frictions have also attracted a lot of attention in the past few years (e.g., Dorofeenko et al., 2008, 2014; Arellano et al., 2012; Christiano et al., 2014; Gilchrist et al., 2014), which is most likely motivated by the recent global economic and financial crisis. For instance, Christiano et al. (2014) include a Bernanke-Gertler-Gilchrist financial accelerator mechanism in a standard

[2]Formerly Chief Economist of the IMF.

monetary dynamic general equilibrium model. In this setup, entrepreneurs transform raw capital into productive capital with uncertainty about the success of the transformation for each entrepreneur prior to the transformation process. Uncertainty is modeled as the time-varying second moment of the technology which converts raw capital into productive capital and only firms with high productive capital experience success. The authors show that this type of uncertainty shock accounts for a large share of the fluctuations in GDP.

While the aforementioned literature are primarily theoretical works on the impact of uncertainty, there are only a limited number of empirical studies in this relatively new strand of literature. The goal of this dissertation is to widen the understanding of the impact of uncertainty on the economy by analyzing empirical data. In particular, the focus of this dissertation lies on quantifying the impact of uncertainty on financial, housing and trade markets.

1.2 The Notion of Uncertainty and Uncertainty Measures

Frank Knight (1921), the famous Chicago economist, provides the modern definition of uncertainty and defines uncertainty as peoples inability to forecast the likelihood of events happening (Knight, 1921). In contrast, he relates risk to the known probability distribution over a set of events. For example, flipping a fair coin does not qualify as uncertain since the likelihood of heads or tails is known; it is, however, risky because there is a 50% chance of obtaining heads with a coin flip (Bloom, 2014). The disentanglement of risk and uncertainty is certainly often not possible with empirical data: Nevertheless, it helps to clarify the difference between risk and uncertainty. In the empirical analyses, however, I follow the literature on uncertainty and use uncertainty measures which also incorporate elements of risk. I refer to Bloom (2014) for a more elaborated discussion of uncertainty and risk.

Uncertainty is an amorphous concept for which no objective measure exists. In the following, I present different economic uncertainty measures which have been used frequently in studies analyzing the impact of uncertainty on the economy. These measures are also used frequently as proxies for different aspects of economic uncertainty in this dissertation.

Macroeconomic uncertainty proposed by Jurado et al. (2015) The macroeconomic uncertainty (*Macro Uncertainty*) measure proposed by Jurado et al. (2015) builds on the unforecastable components of a broad set of macroeconomic variables. Jurado et al. (2015) estimate *Macro Uncertainty* as the conditional standard deviation "of the purely unforecastable component of the future value". More specifically, they calculate for $N_y = 132$ macroeconomic time series $y_{jt} \in Y = y_{1t}, ..., y_{132t}$ the conditional standard deviation of the unpredictable component of the h-step-ahead realization:

$$U_{jt}^{y}(h) = \sqrt{E[(y_{jt+h} - E[y_{jt+h}|I_t])^2|I_t]}, \tag{1.1}$$

where $y_{jt+h} - E[y_{jt+h}|I_t]$ denotes the h-step-ahead forecast error and $E[.|I_t]$ the expectation taken conditional on the information set I_t which is available at time t. The *Macro Uncertainty* is then computed as:

$$U_t^y(h) = \sum_{j=1}^{N_y} \frac{1}{N_y} U_{jt}^y(h). \tag{1.2}$$

To compute $U_{jt}^y(h)$, Jurado et al. (2015) first form factors from a large set of economic and financial[3] indicators, which represent I_t. These factors are used to estimate the expected squared forecast error $E[(y_{jt+h} - E[y_{jt+h}|I_t])^2|I_t]$. This measure captures the predictability of the overall macroeconomic environment; the less predictable the macroeconomic variables, the higher the macroeconomic uncertainty. I use the one-month-ahead measure throughout the dissertation, since the data are at the monthly frequency.

Financial uncertainty proposed by Ludvigson et al. (2016) The computation of the financial uncertainty (*Finance Uncertainty*) measure by Ludvigson et al. (2016) follows Jurado et al. (2015) but is based on 147 financial variables instead of 132 macroeconomic variables.

Economic policy uncertainty proposed by Baker et al. (2016) The economic policy uncertainty (*Policy Uncertainty*) measure proposed by Baker et al. (2016) proxies for movements in policy-related economic uncertainty. The index quantifies the frequency of articles in 10 leading U.S. newspapers

[3] For the computation of *Macro Uncertainty*, Jurado et al. (2015) also include 25 financial variables.

that contain the following triple of words: “economic" or “economy"; “uncertain" or “uncertainty"; and one or more of “congress", “deficit", “Federal Reserve", “legislation", “regulation" or “White House".

Chicago Board Options Exchange Volatility Index The Chicago Board Options Exchange Volatility Index (*VIX*) estimates the 30-day expected volatility of the S&P 500 index. The formula[4] used in the *VIX* calculation is:

$$\sigma^2 = \frac{2}{T}\sum_i \frac{\Delta K}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}[\frac{F}{K_0} - 1]^2, \tag{1.3}$$

where

- T is the time to expiration,
- F the forward index level derived from index option prices,
- K_0 the first strike below the forward index level F,
- K_i the strike price of the i-th out-of-the-money option; a call if $K_i > K_0$; and a put if $K_i < K_0$; both out and call if $K_i = K_0$,
- ΔK_i the interval between strike prices,
- R the risk-free interest rate to expiration,
- $Q(K_i)$ the midpoint of the bid-ask spread for each option with strike K_i,
- and $\sigma = \frac{VIX}{100}$.

The *VIX* is therefore *VIX*$= \sigma * 100$. The underlying components of the *VIX* calculation are put and call options with more than 23 days and less than 37 days to expiration. For a more detailed explanation of the *VIX*, see the “VIX White Paper" on the homepage[5] of the Chicago Board Options Exchange.

[4] The formula is taken from the “VIX White Paper".

[5] https://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/the-vix-index-calculation.

1.3 Descriptive Statistics and Causality of the Uncertainty Measures

Table 1.1 shows the descriptive statistics of the four aforementioned uncertainty measures. Although the computation procedures for *Macro Uncertainty* and *Finance Uncertainty* are the same, the mean as well as the volatility of *Finance Uncertainty* are substantially higher. This reflects the more unpredictable nature of the underlying 147 financial variables compared to the 132 macroeconomic series.

The column ERS (Elliott-Rothenberg-Stock) test statistic contains the test statistics of the Dickey-Fuller GLS unit root test which is proposed by Elliott et al. (1996)[6]. The lag lengths for the individual tests are chosen based on the Schwarz criterion. The null hypothesis of containing a unit root can be rejected for all time series. Moreover, using the Augmented Dickey-Fuller test also leads to the same conclusions.

Figure 1.1 depicts the evolution of the four uncertainty measures over time for the period 1990M1-2015M12, while Table 1.2 displays the cross-correlation of the measures. All uncertainty measures are positively correlated and show dramatic increases during the financial crisis. *Finance Uncertainty* and the *VIX* are particularly highly correlated, which is not surprising, since both measures proxy the financial market uncertainty.

Table 1.1: Summary Statistics of the Uncertainty Measures

	Obs	Mean	Std. Dev.	Min	Max	ERS test statistic
Macro Uncertainty	312	0.664	0.088	0.557	1.083	-3.01***
Finance Uncertainty	312	0.900	0.184	0.643	1.542	-2.92***
Economic Policy Uncertainty	312	106.4	33.87	57.20	245.1	-4.31***
VIX	312	19.834	7.641	10.821	62.642	-4.61***

Descriptive statistics of the uncertainty measures, 1990M1-2015M12.

[6]The authors show that this test dominates the conventional Dickey-Fuller test in terms of small-sample size properties and power.

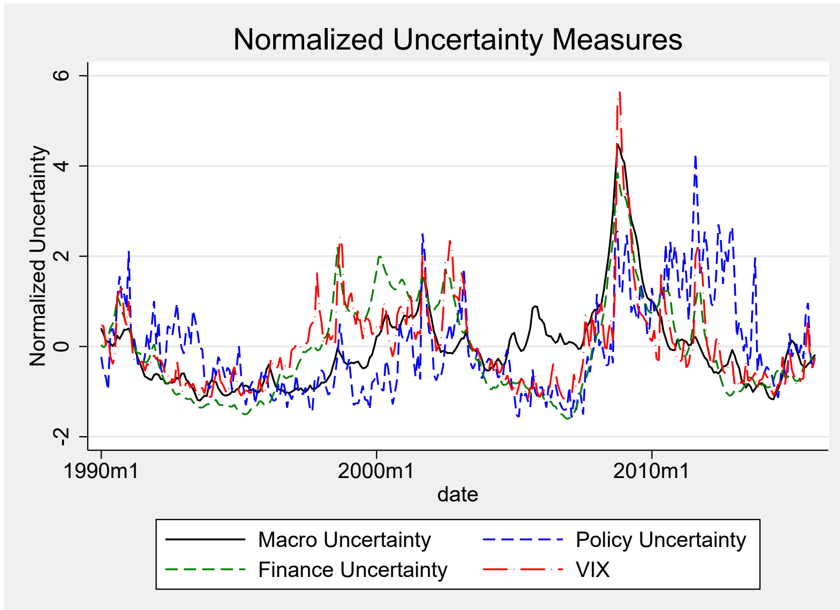

Figure 1.1: Development of the Uncertainty Measures, 1990M1-2015M12.

Table 1.2: Correlation of Uncertainty Measures

	Macro Uncertainty	Finance Uncertainty	Policy Uncertainty	VIX
Macro Uncertainty	1			
Finance Uncertainty	0.714	1		
Policy Uncertainty	0.352	0.381	1	
VIX	0.650	0.853	0.456	1

Correlation of the uncertainty measures, 1990m1-2015M12.

Table 1.3 summarizes the p-value of the Granger causality test results for all uncertainty measures. For example, in order to obtain the test results in column (2), the following equation was estimated[7]:

[7] Two lags are recommended by the Schwarz criterion.

$$MU_t = \sum_{j=1}^{2} \alpha_j MU_{t-j} + \sum_{j=1}^{2} \beta_j FU_{t-j} + \sum_{j=1}^{2} \delta_j PU_{t-j} + \sum_{j=1}^{2} \gamma_j VIX_{t-j} + u_t{}^{8}. \quad (1.4)$$

Subsequently, the null hypotheses $\beta_1 = 0 \& \beta_2 = 0$, $\delta_1 = 0 \& \delta_2 = 0$ and $\gamma_1 = 0 \& \gamma_2 = 0$ were tested to determine if *Finance Uncertainty*, *Policy Uncertainty* and the *VIX* are Granger causal for *Macro Uncertainty*, respectively. Corresponding estimations and tests were also performed to obtain the remaining columns. There is a high level of interconnectedness between the different uncertainty proxies. First, at the 5% significance level, *Macro Uncertainty* is significantly explained by all other measures of uncertainty. Second, *Finance Uncertainty* and the *VIX* significantly affect one another. Moreover, *Finance Uncertainty* helps to predict all remaining uncertainty proxies and, therefore, seems to be an important driver of the overall level of economic uncertainty.

Table 1.3: Granger Causality Tests

	(2) Macro Uncertainty	(3) Finance Uncertainty	(4) Policy Uncertainty	(5) VIX
Macro Uncertainty		0.365	0.800	0.380
Finance Uncertainty	0.016**		0.019**	0.000***
Policy Uncertainty	0.022**	0.025**		0.537
VIX	0.015**	0.005***	0.1343	

Causality tests of the uncertainty measures, 1990m1-2015M12. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

[8] *MU* denotes *Macro Uncertainty*, *FU Finance Uncertainty* and *PU Policy Uncertainty*.

CHAPTER 2

Uncertainty, the Option to Wait and IPO Issue Cycles

Abstract: This paper uses recently developed uncertainty measures to examine the role of economic uncertainty in explaining the U.S. Initial Public Offering (IPO) issue cycles. Time series estimations reveal a strong and robust negative impact of macroeconomic and financial uncertainty on the IPO activity. For instance, an increase in macroeconomic uncertainty by one standard deviation lowers the number of monthly IPOs by roughly four in the long-run, which equals 20% of the average number of monthly IPOs. In response to an uncertainty shock, both the reduction of the number of IPO filings and the rise of withdrawn IPOs contribute to the lower number of IPOs. These results support the view that firms value the option to wait and tend not to go public during periods of high uncertainty, which is akin to the occurrence of the real options effect in periods of high uncertainty if investments are irreversible. However, there is no significant impact of economic policy uncertainty on the IPO market. The study also finds that high uncertainty worsens the IPO market condition by depressing stock prices, output, investor optimism and consumer sentiment.

2.1 Introduction

The cyclical nature of the number of initial public offerings (IPO number) is a highly debated phenomenon. Ibbotson and Jaffe (1975) and Ibbotson et al. (1988, 1994) highlight the substantial fluctuation of new IPO issues and more recent studies provide numerous explanations for the hot and cold IPO markets. Notably, the comprehensive empirical studies of Lowry (2003) and Ivanov and Lewis (2008) identify economic growth, stock market return, investor optimism and consumer sentiment as the most important determinants of IPO number. This paper provides an alternative view and argues that uncertainty surrounding the overall economy is also a key driver of IPO issue cycles.

Figure 2.1 shows the evolution of IPO number and the macroeconomic uncertainty (*Macro Uncertainty*) measure by Jurado et al. (2015) for the period 1981M1-2016M3: there is a negative correlation of -0.43 between the two series and both variables exhibit pronounced cycles. If macroeconomic uncertainty is very high and exceeds for example its 80-th percentile[1], the high level of uncertainty lasts for a considerable amount of periods before it dissolves[2]. For instance, the macroeconomic uncertainty exceeds its 80-th percentile for 32 consecutive months during the financial crisis (2007M10-2010M5); for 28 consecutive months between 1981M1-1983M4 and for 14 consecutive months between 2000M12-2002M1. During those periods of high uncertainty IPO number drops quickly.

In fact, the president of NASDAQ, Adena Friedman, also relates IPO number to uncertainty and states[3]

> "It's an uncertain environment to go public in ..."
> (Wall Street Journal, January 20, 2016.)[4]

to comment the sharp drop in the number of U.S. IPOs by 75% in the first quarter of 2016. However, neither the statistical reliability of the impact

[1] Exceeding its 80-th percentile means that *Macro Uncertainty* is greater than 80% of the values of *Macro Uncertainty* in the sample.

[2] Jurado et al. (2015), Ludvigson et al. (2016) and Lee et al. (2016) have documented and extensively discussed the high persistence of uncertainty shocks.

[3] https://www.wsj.com/articles/nasdaqs-friedman-says-ipo-environment-still-uncertain-1453295483

[4] There are numerous popular press articles which relate IPO activity to uncertainty including the Wall Street Journal, the Financial Times, CNBC and the Washington Post.

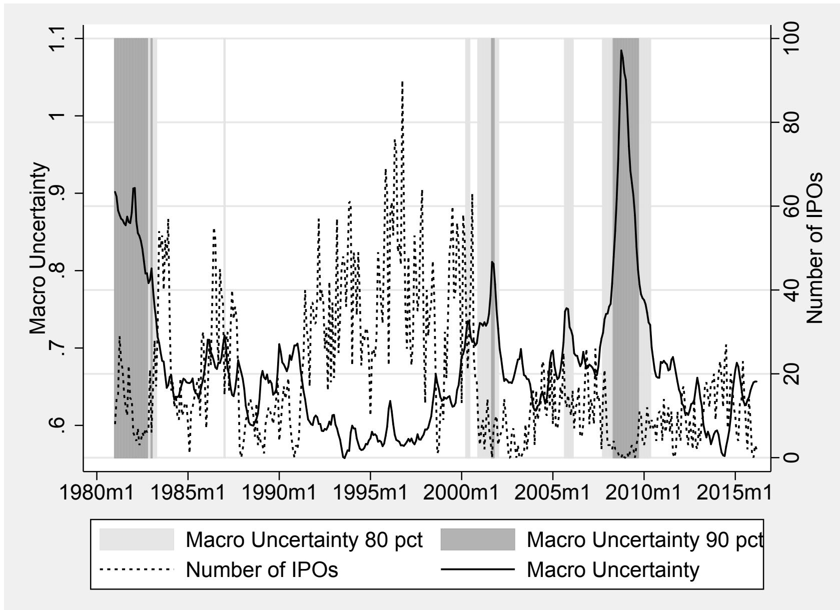

Figure 2.1: *Macro Uncertainty* and the Number of IPOs

Time series of the number of IPOs and *Macro Uncertainty*, 1981M1-2016M3. "Macro Uncertainty 80 pct" and "Macro Uncertainty 90 pct" denote the periods in which *Macro Uncertainty* is greater than 80% and 90% of the values of *Macro Uncertainty* in the sample, respectively. Data on IPO number are provided by Jay Ritter (https://site.warrington.ufl.edu/ritter/ipo-data/), while *Macro Uncertainty* is collected from the website of Sydney Ludvigson (http://www.sydneyludvigson.com/data-and-appendixes/).

of economic uncertainty on the IPO activity nor the mechanisms of impact have been examined. The lack of appropriate uncertainty measures may have hindered an in-depth statistical analysis. This study fills this gap by using recently developed uncertainty measures and evaluate their impact on the IPO market. More specifically, I use the *Macro Uncertainty* by Jurado et al. (2015), the *Finance Uncertainty* by Ludvigson et al. (2016), the *Policy Uncertainty* by Baker et al. (2016) and the *VIX* to quantify the impact of uncertainty on the IPO number, the number of filed IPOs and the number of withdrawn IPOs. Moreover, I also present a stylized model in which the impact mechanisms of uncertainty on the IPO decision can be retraced. The model considers an IPO as an irreversible investment with the possibility of delay, and borrows from the literature on irreversibility of investment and uncertainty (e.g., Pindyck, 1991; Bloom, 2009).

Using the sample period 1990M1-2015M12 and controlling for a broad set of IPO market determinant variables, I find that a one standard deviation increase in macroeconomic uncertainty decreases IPO number by roughly four, which is 20% of the average number of IPOs per month. This result is driven by both the reduction of the number of filed IPOs and the rise of the number of withdrawn IPOs, and suggests that firms value the option of waiting instead of immediately going public during periods of high uncertainty. Furthermore, I find that uncertainty also distresses the overall IPO market condition by depressing stock prices, output, investor optimism and consumer sentiment. The results are qualitatively similar and robust for the *VIX*, *Macro Uncertainty* and *Finance Uncertainty* in numerous specifications. *Policy Uncertainty*, however, does not display a significant effect on the IPO activity.

2.1.1 Related IPO Literature

Numerous explanations for the hot and cold IPO markets have been proposed in the finance literature. Ritter (1991) relates IPO waves to the sentiments of investors, whereas Rajan and Servaes (1997) note that more firms complete IPOs when analysts are overoptimistic. Choe et al. (1993) and Yung et al. (2008) focus on the role of adverse selection but arrive at contradicting conclusions, since they make different assumptions about the serial dependence of innovation. However, the results of Helwege and Liang (2004) suggest that hot markets are not driven by adverse selection costs but are more likely affected by greater investor optimism. Lowry and Schwert (2002), Benveniste et al. (2003) and Alti (2005) highlight the role of information spillovers of pioneer IPOs which facilitate the pricing of subsequent issues and thus attract more firms to the IPO market. Pástoră and Veronesi (2005) emphasize the importance of firms' expectation about (aggregated) profitability in explaining IPO number and Chemmanur and He (2011) argue that firms go public to grab market share from competitors after a productivity shock. The comprehensive studies of Lowry (2003) and Ivanov and Lewis (2008) test the empirical relevance of numerous explanations and identify past initial returns of IPOs, economic growth, stock market return, the term spread, the optimism of investors and consumer sentiment as the most important determinants of IPO number. I, thefore, include theses factors as control variables in the regression analyses.

2.1.2 The Impact Mechanism of Uncertainty on the IPO Decision

Typically the literature on uncertainty distinguishes between uncertainty and risk; risk is related to the known probability distribution over a set of events, whereas uncertainty is associated with peoples' inability to forecast the likelihood of events happening (Knight, 1921). In this context, flipping a fair coin is not uncertain, since the likelihood of head or tail is known, but it is risky because there is a 50% chance to obtain head with a coin flip (Bloom, 2014). The disentanglement of risk and uncertainty is certainly often not possible with real world data. Nevertheless, it helps to clarify the difference between risk and uncertainty, and therefore facilitates the theoretical consideration of how uncertainty might affect the IPO decision in the current subsection. In the empirical analysis, however, I follow the literature on uncertainty and use uncertainty measures which also incorporate elements of risk.

Economic uncertainty could impact the IPO activity through different ways. First of all, given the irreversible nature of an IPO and the option to go public at a different point in time, high uncertainty may increase the option value of waiting of firms which consider the timing of their IPOs. For instance, a firm goes public only if it expects to raise at least as much capital as the firm is worth. However, if an uncertainty shock occurs and the firm is uncertain about how much it can expect to raise from the IPO, the firm may delay the IPO until uncertainty subsides. In addition, Lowry (2003) finds that firms go public if the business outlook is good and their demand for new capital to boost investment is high. If firms are uncertain about the economic development and thus uncertain about their own capital demand and associated new investments, they may wait and gather more information instead of immediately going public to raise capital for new investments. The reasoning that firms decrease investments in periods of high uncertainty is also supported by numerous studies (e.g., Bernanke, 1983; Pindyck, 1991; Gulen and Ion, 2015).

The rationale that firms tend not to go public in periods of high uncertainty is consistent with the occurrence of the real options effect due to uncertainty if investments are irreversible as described in Pindyck (1991): "There will be a value to waiting (i.e., an opportunity cost to investing today rather than waiting for information to arrive) whenever the investment is irreversible and the net payoff from the investment evolves stochastically over time". In other words, when a firm makes an irreversible investment expenditure, it essentially gives up the possibility of waiting for new information that might affect the desirability or timing of the expenditure; it cannot disinvest should market conditions change adversely. Going public also represents a form of "irreversible investment", since a firm typically has only one IPO with an associated payoff which depends on the (time-varying) market condition. The higher the uncertainty about the market conditions, the more valuable the option to wait. A comparable waiting attitude can also be observed in the merger market as suggested by Bhagwat et al. (2016). They find that a one standard deviation increase in the *VIX*, a proxy for financial uncertainty, is associated with a 6% drop in public merger deal activity. Similarly, Jovanovic and Rousseau (2001) highlight the value of waiting in the IPO market. In their model, however, the option to delay an IPO is valuable if waiting allows a firm to gather more information about its own production function.

Figure 2.2 illustrates a stylized model of a firm's decision about the timing of its IPO and how uncertainty might affect this decision. Consider a firm with a true firm value of \$100, and this firm could raise \$120 (good market condition) with probability of p and \$80 (bad market condition) with probability $1-p$ in an IPO. According to the notion of risk and uncertainty from above, going public is risky in general but not uncertain. It takes one period of time to prepare the IPO. For example, if in $t=0$ the firm decides to go public the factual IPO takes place in $t=1$. The firm decides to go public only if it expects to raise at least as much capital as the firm is worth. For simplicity, the discount rate is zero. In $t=0$, if there is no uncertainty at all, the firm assigns a value to p and decides to go public if $p \geq 50\%$. However, if there is a one-period uncertainty shock in $t=0$ in the spirit of Knight (1921), the firm is not able to assign a value to p and postpones the IPO decision to period $t=1$ when the uncertainty shock subsides.

Analogously, if all IPO-interested firms are homogeneous and are all hit by the same one-period uncertainty shock in period $t=0$, there will be no IPOs in $t=1$. As the uncertainty shock disappears in $t=1$ and $p \geq 0.5$, all firms go public in $t=2$. For a set of heterogeneous firms a common uncertainty shock may still reduce the number of IPOs in the subsequent period if a fraction of those firms experience the shock similarly.

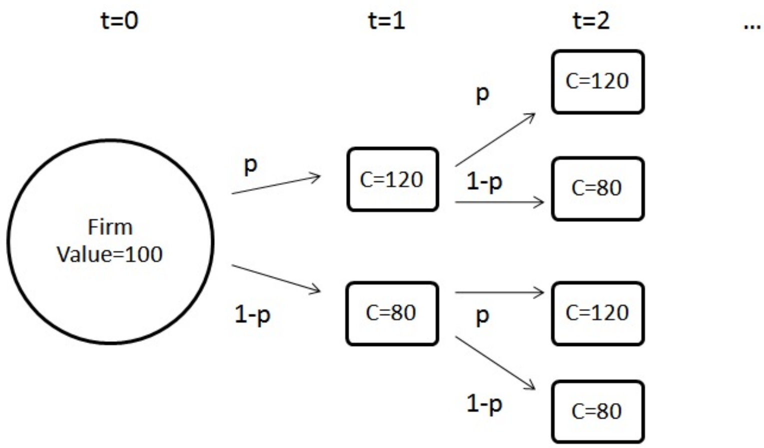

Figure 2.2: Real Option of Waiting

p is the probability to raise $120 as capital (C) in an IPO.

As suggested by Figure 2.1 and the literature on uncertainty, high uncertainty shocks are persistent and thus are likely to impede the IPO number for a considerable amount of time contributing to the creation of cold IPO market phases. As uncertainty eventually dissolves, IPO-interested firms start to go public in the same time slot, which in turn could give rise to IPO hot market phases.

Last but not least, high uncertainty could overshadow the IPO market condition by deteriorating the business outlook. For instance, Bloom (2009), Bansal et al. (2014) and Christiano et al. (2014) conclude that high uncertainty decreases output, consumption and investment[5], while other studies find that uncertainty is negatively related to aggregated growth and asset prices (e.g., Ozoguz, 2009; Pástoră and Veronesi, 2012; Segal et al., 2015). As pointed out by Pástoră and Veronesi (2005) and Pástor et al. (2009), firms tend to go public if the expected (aggregate) profitability is high. Therefore,

[5]Some other studies on the impact of uncertainty on the real economy are Bernanke (1983), Pindyck (1991), Caballero and Pindyck (1996), Bachmann and Bayer (2013), Caggiano et al. (2014), Dorofeenko et al. (2014) and Leduc and Liu (2016). See Bloom (2014) for a more comprehensive review of the literature on uncertainty.

IPO-interested firms may anticipate a decline in expected profitability following an uncertainty shock and choose not to go public during periods of high uncertainty. In context of the presented stylized model, following an uncertainty shock a decline of the business outlook may translate to a decrease of p and a decline of the payoffs in good and bad IPO market conditions. Both the drop of the probability to raise capital in a good market condition and the fall of the potential payoffs make firms less willing to go public.

The rest of the paper is organized as follows. Section 2.2 describes the data, analyses the time-series properties of the key variables and presents the econometric model. Section 2.3 examines the impact of uncertainty on the IPO activity. Section 2.4 investigates the effects of uncertainty on IPO market condition variables including S&P 500 return, output growth, investor optimism and consumer sentiment. Finally, section 2.5 concludes.

2.2 Data and Econometric Specification

The sample for this study is 1990M1-2015M12[6] and include monthly data on IPO activity, four different uncertainty measures and numerous control variables. Detailed information on the data is presented in the Appendix.

2.2.1 IPO Activity Data

The number of IPOs per month and the average, equal-weighted monthly IPO initial returns are fetched from the Ibbotson, Sindelar and Ritter (ISR) database. The initial returns represent the mean, across all IPOs each month, of the percentage difference between a closing price within the first month after the IPO and the offer price. A more complete description of the construction of the data is in Ibbotson et al. (1994). Data on the number of filed IPOs and the number of withdrawn IPOs are provided by NASDAQ, and cover IPO activity on the NYSE and the NASDAQ for the period 1997M1-2015M12.

[6]Since the VIX and the monthly GDP data are not available for earlier periods. However, analyses with the sample 1980M1-2015M12 omitting monthly GDP deliver qualitatively the same results for *Macro Uncertainty* and *Finance Uncertainty*.

2.2.2 Uncertainty Measures

Finding an appropriate uncertainty measure is a challenging task, since uncertainty is an amorphous concept for which no objective measure exists. This study uses four uncertainty proxies which are based on different approaches to approximate the latent stochastic process of uncertainty including *Macro Uncertainty* (Jurado et al., 2015), *Finance Uncertainty* (Ludvigson et al., 2016), *Policy Uncertainty* (Baker et al., 2016) and the *VIX*.

The *Macro Uncertainty* by Jurado et al. (2015) captures the predictability of the overall macroeconomic environment; the less predictable the macroeconomic variables, the higher the macroeconomic uncertainty. I decided to use the one-month-ahead measure, since the data are at a monthly frequency. The computation of *Finance Uncertainty* (Ludvigson et al., 2016) follows Jurado et al. (2015) but uses 147 financial variables instead of 132 macroeconomic variables as before. The *Policy Uncertainty* measure by Baker et al. (2016) proxies for movements in policy-related economic uncertainty by quantifying the frequency of articles in 10 leading U.S. newspapers which contain certain combinations of key words on economic policy uncertainty. The *VIX* estimates the 30-day expected volatility of the S&P 500 index. See section 1.2 for a more detailed description of the four uncertainty measures.

One could argue that the presented uncertainty measures capture a mixture of both uncertainty and risk. However, since these measures are frequently applied in studies that examine the effects of (economic) uncertainty, I refrain from disentangling (Knightian) uncertainty and risk in the empirical part of the current paper and refer to a broader definition of uncertainty which also incorporates components of risk.

According to Lowry (2003), Pástoră and Veronesi (2005) and Ivanov and Lewis (2008), firms consider the condition of both the real economy and the financial market before they go public. *Macro Uncertainty*, which also incorporates uncertainty components of 25 financial variables, may therefore be the most potent uncertainty measure to explain the IPO activity, since it incorporates uncertainty about the real economy and the financial market.

2.2.3 Descriptive Statistics

Table 2.1 displays descriptive statistics of the IPO activity variables and the measures of uncertainty. There is substantial variation of the IPO number as well as of the number of filed IPOs. The number of withdrawn IPOs reached its all time high of 40 in March 2001, in a period in which Macro Uncertainty exceeds its 90th percentile. Although the computation procedures for *Macro Uncertainty* and *Finance Uncertainty* are the same, the mean as well as the volatility of Finance Uncertainty are substantially higher. This reflects the more unpredictable nature of the underlying 147 financial variables used for the computation of *Finance Uncertainty* compared to the 132 macroeconomic series[7] which underlie the computation of *Macro Uncertainty*.

The column ERS (Elliott-Rothenberg-Stock) test statistic contains the test statistics of the Dickey-Fuller GLS unit root test which is proposed by Elliott et al. (1996)[8]. The lag length for the individual tests are chosen with respect to the Schwarz criterion. The null hypothesis of containing a unit root can be rejected for all time series. Using the Augmented Dickey-Fuller test leads to the same conclusions. The finding that IPO number is stationary is very much in line with Ivanov and Lewis (2008) who also use monthly data.

The cross-correlation of the uncertainty measures and the IPO number are presented in Table 2.2. Although the different uncertainty measures may capture different aspects of economic uncertainty, they are highly positively correlated indicating common sources of uncertainty or/and spillover effects of one type of uncertainty on another. *Finance Uncertainty* and the *VIX* exhibit a notably high correlation of 0.85, which is not surprising, since the *VIX* also proxies uncertainty surrounding the financial market. Moreover, all uncertainty measures are strongly negatively correlated with the number of initial public offerings suggesting an inverse relation between uncertainty and IPO activity.

[7] The 132 macroeconomic variables already contain 25 of financial indicators.

[8] The authors show that this test dominates the conventional Dickey-Fuller test in terms of small-sample size properties and power.

Table 2.1: Summary Statistics of IPO Activity Variables and Uncertainty Measures

	Obs	Mean	Std. Dev.	Min	Max	ERS test statistic
Number of IPOs (IPO number)	312	19.669	17.562	0	100	-2.21**
Number of filed IPOs	228	36.236	19.824	5	128	-3.03***
Number of withdrawn IPOs	228	8.820	6.896	0	40	-6.84***
Macro Uncertainty	312	0.664	0.088	0.557	1.083	-3.01***
Finance Uncertainty	312	0.900	0.184	0.643	1.542	-2.92***
Policy Uncertainty	312	106.43	33.87	57.20	245.12	-4.3***
VIX	312	19.834	7.641	10.821	62.642	-4.61***

Sample statistics on IPO number, *Macro uncertainty*, *Finance uncertainty*, *Policy uncertainty* and *VIX* for the period 1990M1-2015M12. Sample statistics on the number of filed IPOs and the number of withdrawn IPOs for the period 1997M1-2015M12. Data on the number of filed IPOs and the number of withdrawn IPOs are provided by NASDAQ. ERS test statistic denotes the test statistics of the Dickey-Fuller GLS unit root test proposed by Elliott et al. (1996). The null hypothesis of containing a unit root can be rejected for all time series variables. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

Table 2.2: Correlation of IPO Number and the Uncertainty Measures

	Number of IPOs	*Macro Uncertainty*	*Finance Uncertainty*	*Policy Uncertainty*	*VIX*
Number of IPOs	1				
Macro Uncertainty	-0.508	1			
Finance Uncertainty	-0.312	0.714	1		
Policy Uncertainty	-0.477	0.352	0.381	1	
VIX	-0.327	0.649	0.852	0.456	1

Correlation of the IPO number and uncertainty measures, 1990M1-2015M12.

2.2.4 Control Variables in Estimations

The results of Lowry (2003) and Ivanov and Lewis (2008) suggest that the business condition, the investor and the consumer sentiments are the most important drivers of IPO cycles[9]. Demand for capital should be higher when business conditions are more promising. For example, firms have higher demand for capital in order to make (new) investments in times of economic growth, and if the financing costs from traditional bank loans are too high, the firms may raise money from the public. Moreover, companies are more likely to go public if investors are overoptimistic and willing to pay more for those companies than they are worth. For example, Lee et al. (1991) and Rajan and Servaes (1997) find that investor sentiment affect the IPO activity over time. Additionally, Lowry and Schwert (2002) find a robust and significant impact of past average initial returns on the IPO number. This relationship is attributed to the information learned during the registration period. In particular, they argue that more companies file IPOs following periods of high initial returns because the high returns are linked to positive information learned during the registration periods, indicating that companies can raise more money in an IPO than they had previously thought.

Accounting for the findings of the literature, I include the S&P 500 return, the real GDP growth, the real industrial production growth, the term structure, the average initial return, the investor sentiment and the consumer sentiment as control variables.

2.2.5 Econometric Specification

Given the stationarity of the IPO activity variables and the uncertainty measures, the following econometric model is estimated:

$$IPONumber_t = \beta_0 + \sum_{i=1}^{k} \alpha_i IPONumber_{t-i} + \sum_{i=1}^{k} \beta_i Uncertainty_{t-i} + \sum_{i=1}^{k} \mathbf{X}_{t-i} \boldsymbol{\delta}_i + u_t, \tag{2.1}$$

where $IPONumber$ is the number of IPOs, $Uncertainty$ denotes the chosen uncertainty measure, $\mathbf{X}_{t-i}$ is a vector containing the aforementioned control variables in $t-i$ and $\boldsymbol{\delta}_i$ is the corresponding coefficient vector.

[9]See Lowry (2003) for further discussions of how the business condition and investor sentiment affect the number of firms going public.

In order to guard against endogeneity issues, all explanatory variables are lagged. I include the first three lags of all explanatory variables in the benchmark specification. Three lags are a conservative choice, since a large set of explanatory variables are included. Using monthly data, Lowry and Schwert (2002) include three lags in a model with two explanatory variables, while Ivanov and Lewis (2008) use up to two lags. In specifications with two or one lag(s) the impact of the uncertainty measures are even more significant[10].

I present the long-run effects of each variable in the estimation results section to ease interpretation[11]. For example, instead of presenting every individual $\hat{\beta}_i$ coefficient of the impact of uncertainty, I present the long-run impact of uncertainty $\sum_{i=1}^{3} \hat{\beta}_i$ and the corresponding standard error.

2.3 Uncertainty and IPO Activity

This section investigates the impact of economic uncertainty on IPO activity. Throughout the remainder of the paper, Newey-West standard errors (Newey and West, 1987) are used in order to account for possible heteroskedasticity and autocorrelation of the error term. I decided to use *Macro Uncertainty* as the measure in the benchmark specification, since it quantifies the overall macroeconomic uncertainty including uncertainty about financial and real variables. Note that the initial return is missing in months when no IPOs occur.

2.3.1 The Impact of Uncertainty on the Number of IPOs

Table 2.3 displays the impact of *Macro Uncertainty* on the number of IPOs per month controlling for a large set of variables. Column (1) represents the benchmark specification with *Macro Uncertainty* as uncertainty measure and all control variables included, while the other columns present alternative specifications. *Macro Uncertainty* significantly impedes IPO number throughout specifications and its impact magnitude also remains moderately constant. A standard deviation increase in *Macro Uncertainty* lowers the

[10]The results are presented in the Appendix.

[11]Presenting estimations of a large set of explanatory variables with there corresponding first three lags in one table may be confusing and impedes readability.

number of IPOs on average by roughly four IPOs[12]. Moreover, specifications with *Macro Uncertainty* always dominate corresponding specifications without it in terms of explanatory power as suggested by the adjusted R, the Akaike criterion and the Schwarz criterion.

Column (2) presents the estimation results for a specification without *Macro Uncertainty*. Naturally, the adjusted R falls and the Akaike criterion and the Schwarz criterion rise in this specification compared to column (1), which indicates that *Macro Uncertainty* has a very high explanatory power. In absence of *Macro Uncertainty* in column (2), the consumer sentiment gains more explanatory power and its long-run coefficient and t-statistic increase, so that its impact even becomes significant at the 10% significance level. This result indicates a notable dependence between *Macro Uncertainty* and the consumer sentiment and suggests that the explanatory power of consumer sentiment is based on its considerable correlation with *Macro Uncertainty*; the correlation is -0.44.

There is also a significant autoregressive component in the IPO number itself. Alti (2005) provides a possible explanation for this finding. He argues that the outcomes of pioneers' IPOs contain private information on common valuation factors of investors. This facilitates the pricing of subsequent issues and attracts more firms to go public soon after. The level of initial return also has a significant impact on the number of IPOs in the benchmark specification. Lowry and Schwert (2002) attribute this relationship to the information learned during the registration period. Moreover, S&P 500 returns show a significant impact on the IPO number, which reflects that the number of IPOs increases if the financial market returns are higher. In summary, the significant impact of the control variables are very much in line with Lowry and Schwert (2002), Lowry (2003) and Ivanov and Lewis (2008).

To compare the impact of *Macro Uncertainty* with those of the other uncertainty measures, Table 2.4 displays the impact of each uncertainty measure on the number of IPOs in the benchmark specification with all control variables. Both financial market uncertainty indicators *Finance Uncertainty* and the *VIX* have statistically significant adverse effects on the number of IPOs. In economic terms, a one standard deviation increase in *Finance Uncertainty* and the *VIX* decrease the number of IPOs on average in the long-run

[12] $(\sum_{i=1}^{3} \hat{\beta}_{i,MacroUncertainty}) * \hat{\sigma}_{MacroUncertainty} = -39.7 * 0.088 \approx 3.5$, where $\hat{\sigma}_{MacroUncertainty}$ is the standard deviation of Macro Uncertainty

Table 2.3: Time Series Analysis of IPO Number

Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Macro Uncertainty	-39.7***		-41.1***		-44.4***	
	(12.83)		(11.91)		(12.90)	
Control variables						
IPO number	.7730***	.7634***	.7774***	.8261***	.7797***	.8670***
	(.0578)	(.0624)	(.0611)	(.0613)	(.0591)	(.0542)
Underpricing	.0676**	.0394	.0734*	.0509	.0794*	.0657
	(.0326)	(.0496)	(.0417)	(.0472)	(.0463)	(.0488)
Term structure	.0095	.3848	-.149	.5127	-.294	.4756
	(.6255)	(.6684)	(.5426)	(.6411)	(.5850)	(.5898)
SP 500 return	70.95*	85.78*	56.75*	101.0**		
	(39.88)	(44.46)	(31.71)	(43.10)		
Industrial production growth	88.70	443.9*	79.83	311.3		
	(246.1)	(247.6)	(241.1)	(242.0)		
GDP growth	-400.	-249.	-400.	-287.		
	(295.7)	(281.4)	(275.3)	(282.3)		
Consumer sentiment	.0426	.1616*			-.047	.0189
	(.1002)	(.0948)			(.0830)	(.0803)
Investor sentiment	-3.31	-7.71			4.643	3.478
	(8.119)	(8.332)			(6.545)	(6.704)
N	257	257	257	257	279	279
Adjusted R	.6647	.6192	.6699	.6427	.6616	.6371
Akaike Criterion	4.776	4.889	4.740	4.829	4.716	4.776
Schwarz Criterion	5.163	5.221	5.044	5.175	4.950	4.971

The table shows regressions in which the number of IPOs is the dependent variable. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1992M1-2015M12, since the monthly GDP variables are not available prior to 1992. Regressions with a sample 1990M1-2015M12 without GDP growth deliver very similar results.

by roughly three and three, respectively[13]. This result is intuitive, since a firm wants to raise as much public capital as possible in an IPO and high financial market uncertainty is likely to depress investors' willingness to invest. The impact of *Policy Uncertainty* is, however, only significant at the 10% significance level and the estimation with *Policy Uncertainty* shows the lowest explanatory power as indicated by the Adjusted R, Akaike criterion and Schwarz criterion. In contrast, *Macro Uncertainty* contains the highest explanatory power which supports the view that firms take into account the uncertainty from the real economy and the financial market when they

[13]*Finance Uncertainty*: $(\sum_{i=1}^{3}\hat{\beta}_{i,FinanceUncertainty}) * \hat{\sigma}_{FinanceUncertainty} = 15.01 * 0.184 \approx 2.76$. *VIX*: $(\sum_{i=1}^{3}\hat{\beta}_{i,VIX}) * \hat{\sigma}_{VIX} = 0.447 * 7.641 \approx 3.41$.

consider an IPO. The finding that *Macro Uncertainty* is the most important uncertainty driver of IPO activity is further supported by Table 2.5, which shows the estimation results of a specification in which all control variables and all uncertainty measures are included. In this specification, only the macroeconomic uncertainty measure displays a significant negative impact on the IPO number.

Given the robust negative impact of uncertainty on the IPO number, a persistent and high uncertainty shock could impede the IPO activity for a considerable amount of periods. As high uncertainty disappears IPO-interested firms, who valued the option to wait during periods of high uncertainty, start to go public in the same time slot. The empirical results strongly support the view that time-varying uncertainty is an important driver of IPO issue cycles.

Table 2.4: The Individual Impact of Different Uncertainty Measures on IPO Number

Uncertainty measure	Impact on IPO number	N	Adjusted R	Akaike Criterion	Schwarz Criterion
Macro Uncertainty	-39.7*** (12.838)	257	.6647868	4.776425	5.163095
Finance Uncertainty	-15.01*** (4.9390)	257	.6532018	4.810401	5.197072
Policy Uncertainty	-.0418* (.02294)	257	.6419197	4.842416	5.229085
VIX	-.4469*** (.14168)	257	.6536126	4.809216	5.195886

The table shows the individual impact of the different uncertainty measures on the number of IPOs. The control variables in all estimations are the first three lags of S&P 500 return, GDP growth, industrial production growth, term structure, consumer sentiment and investor sentiment. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1992M1-2015M12, since the monthly GDP variables are not available prior to 1992. Regressions with a sample 1990M1-2015M12 without GDP growth deliver very similar results.

Table 2.5: The Simultaneous Impact of Different Uncertainty Measures on IPO Number

Uncertainty measure	Impact on IPO number
Macro Uncertainty	-45.17**
	(18.461)
Finance Uncertainty	1.9730
	(11.082)
Policy Uncertainty	-.0490
	(.04182)
VIX	-.1588
	(.29643)
N	257
Adjusted R	.66656
Akaike Criterion	4.8008
Schwarz Criterion	5.3118

The table shows the impact of the different uncertainty measures on the number of IPOs in a model where all uncertainty measures and control variables are included . The control variables in all estimations are the first three lags of S&P 500 return, GDP growth, industrial production growth, term structure, consumer sentiment and investor sentiment. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1992M1-2015M12, since the monthly GDP variables are not available prior to 1992. Regressions with a sample 1990M1-2015M12 without GDP growth deliver very similar results.

2.3.2 The Impact of Uncertainty on the IPO Timing

In general, companies and/or underwriters have three ways to influence the timing of an IPO. First, companies can choose the time to file the issue. Second, the planned issue date can be changed. Third, they can withdraw the issue. The strong negative relationship between uncertainty and the subsequent number of IPOs indicate that firms time their IPOs in response to the level of uncertainty. This subsection sheds light on the IPO timing of firms and investigates the relation between uncertainty and the number of IPO filings and the number of withdrawn IPOs.

Table 2.6 presents the estimation results for the number of filed and the number of withdrawn IPOs which are explained by different uncertainty measures, controlling for the whole available set of control variables from Equation (2.1). In other words, the $IPONumber$ from Equation (2.1) is replaced by the number of filed and the number of withdrawn IPOs, respectively. Here, the number of withdrawn IPOs are weighted by the sum of the number of filed IPOs in the four previous months. This weighting approach is analogous to Lowry and Schwert (2002) and scales the number of withdrawn IPOs by the number of firms which could have possibly withdrawn their IPOs[14]. However, no weighting or weighting with less than four months lead to the same qualitative conclusion. I include the first two lags of all explanatory variables, considering the smaller sample size and the recommendation of the Schwarz criterion.

All uncertainty measures have significant negative impact on the IPO timing, except for *Policy Uncertainty*. The insignificance of *Policy Uncertainty* is expected, since *Policy Uncertainty* does not impact the IPO number significantly in the analysis of the previous subsection. An increase in uncertainty leads to a lower number of firms who file an IPO and raises the number of withdrawn IPOs. The latter is particularly notable, since withdrawing an IPO has numerous associated costs. First, withdrawing an IPO may delay profitable investment due to financing shortage. This cost is particularly high for firms in nascent industries in which an early entrance ensures first-mover advantages. A second cost of withdrawing an IPO is the increased uncertainty about the firm valuation and an associated bad reputation, which may hinder raising capital from the public securities markets in the future. Lerner (1994) argues that even if the stated reason for the IPO withdrawal is poor market conditions, the firm may still be lumped with other companies whose offerings did not sell because of questionable accounting practices or gross overpricing. In the same vein, Dunbar and Foerster (2008) discover that only about 9% of withdrawn IPOs are able to return to have a successful IPO and Lian and Wang (2009) find that the negative connotations of the first-time withdrawal translate into lower valuations for second-time IPOs. Therefore, high uncertainty seems to be of significant importance to the firms, so that they withdraw their IPO in response to an uncertainty shock despite the potential withdrawal costs.

[14]By using the scaled number of withdrawn IPOs in the regression, the magnitude of impact cannot be easily calculated. However, the sign and significance of impact can still be interpreted straightforwardly: A positive and significant coefficient of uncertainty indicates that an increase in uncertainty leads to an increase in withdrawn IPOs on average.

Table 2.6: The Impact of Different Uncertainty Measures on Number of Filed IPOs and Number of Withdrawn IPOs

Uncertainty measure	Impact on Number of filed IPOs	Impact on the weighted Number of withdrawn IPOs	N
Macro Uncertainty	-43.92***	.16705**	205
	(15.498)	(.06942)	
Finance Uncertainty	-11.25**	.07937***	205
	(5.1210)	(.02894)	
Policy Uncertainty	-.0093	.00006	205
	(.02840)	(.00012)	
VIX	-.4245**	.00198**	205
	(.16599)	(.00093)	

The table shows the individual impact of the different uncertainty measures on the number of filed IPOs and number of withdrawn IPOs. The control variables in all estimations are the first three lags of S&P 500 return, GDP growth, industrial production growth, term structure, consumer sentiment and investor sentiment. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1997M1-2015M12.

2.3.3 Robustness Checks

The empirical results are qualitatively similar under numerous specifications. Specifically, I use different lag specifications, include the NBER recession dummy, include the business condition variables as leads, exclude some explanatory variables, include an alternative investment sentiment measure[15], perform F-test on the joint impact of the lags of each explanatory variable and alternate the maximum lag of autocorrelation in the error term. Moreover, estimations of corresponding autoregressive conditional count models also deliver qualitatively comparable results. Estimation methods include Poisson Maximum-Likelihood, Binomial Maximum-Likelihood, Exponential

[15]The alternative investment sentiment measure is computed by using the data on the fraction of bullish investors minus the fraction of bearish investors from Investors Intelligence (http://www.investorsintelligence.com/x/default.html).

Quasi-Maximum-Likelihood and Normal Quasi-Maximum-Likelihood. Last but not least, I estimate the impact of *Macro Uncertainty* and *Finance Uncertainty* with the sample 1981M1-2015M12 without monthly GDP as control variable and obtain similar results[16].

2.4 Uncertainty and the IPO Market Conditions

The finding that companies do not go public and even cancel their IPO issue in response to high uncertainty suggests that uncertainty may have a depressing effect on the (subsequent) IPO market condition. Therefore, this section investigates the impact of uncertainty on the variables which are considered to be the key determinants of the IPO market conditions (e.g., Lowry, 2003; Ivanov and Lewis, 2008). Table 2.7 presents the correlations of *Macro Uncertainty* with the IPO market condition variables. *Macro Uncertainty* is negatively correlated with all market condition variables, while the market condition variables are positively correlated with each other.

Table 2.7: Correlation of Macro Uncertainty and IPO Market Determinants

	Macro Uncertainty	S&P 500 return	Ind. Production growth	GDP growth	Investor sentiment	Consumer sentiment
Macro Uncertainty	1					
S&P 500 return	-0.201	1				
Ind. Production growth	-0.422	-0.005	1			
GDP growth	-0.155	0.0939	0.216	1		
Investor sentiment	-0.263	0.442	0.170	0.154	1	
Consumer sentiment	-0.440	0.121	0.232	0.131	0.503	1

Correlation of Macro uncertainty and IPO market determinants for the period 1992M1-2015M12.

[16] The estimation results for $MacroUncertainty$ are presented in the Appendix.

For each of the key variables (S&P 500 return, industrial production growth, GDP growth, investor and consumer sentiment) the following regression equation is estimated:

$$y_t = \beta_0 + \sum_{i=1}^{k} \alpha_i y_{t-i} + \sum_{i=1}^{k} \beta_i Uncertainty_{t-i} + \sum_{i=1}^{k} \mathbf{X}_{t-i} \boldsymbol{\delta}_i + u_t, \qquad (2.2)$$

where y denotes a key variable, $Uncertainty$ the uncertainty measure and $\mathbf{X}_{t-i}$ the vector of control variables which contains the remaining key variables in $t-i$.

Table 2.8 summarizes the (long-run) impact of the different measures of uncertainty on the IPO market determinants. In the third column the impact of the uncertainty measures on the stock market return is presented. *Macro Uncertainty* and *Finance Uncertainty* adversely affect the S&P 500 returns. This result is consistent with Segal et al. (2015), who find that uncertainty, which is associated with negative innovation, decreases asset prices. Industrial production is negatively affected by a rise in *Macro Uncertainty*, *Finance Uncertainty* and the *VIX*. Bloom (2009) also finds that an increase of the *VIX* leads to a drop in output. However, GDP growth and investor sentiment are only significantly affected by Macro Uncertainty, while only *Policy Uncertainty* has a significant impact on consumer sentiment.

The different uncertainty measures capture different aspects of economic uncertainty and therefore have different impacts on the economic and sentiment variables. Among them *Macro Uncertainty* is the strongest predictor of the IPO market determinants. In fact, *Macro Uncertainty* also performs best in explaining IPO activity in section 2.3 in terms of significance and explanatory power. These results strongly encourage the reasoning that firms consider the uncertainty of real and financial variables when they plan to go public.

Table 2.8: The Impact of Different Uncertainty Measures on IPO Market Determinants

Uncertainty Measure	N	S&P 500 return	Ind. production growth	GDP growth	Investor sentiment	Consumer sentiment
Macro Uncertainty	285	-.113***	-.028***	-.009**	-.150**	-2.868
		(.04061)	(.01050)	(.00457)	(.07604)	(2.4304)
Finance Uncertainty	285	-.033**	-.007**	-.0025	-.0163	.03928
		(.01557)	(.00310)	(.00176)	(.03391)	(1.0204)
Policy Uncertainty	285	.00014	0.000	0.000	.00024	-.019**
		(.00009)	(.00002)	(.00001)	(.00024)	(.00963)
VIX	285	.00011	-.00017**	-.0000	.00030	.03649
		(.00041)	(.00008)	(.00004)	(.00077)	(.02307)

The table shows the individual impact of the different uncertainty measures on the business condition and sentiment variables. The control variables in all estimations are the lags of S&P 500 return, GDP growth, industrial production growth, consumer sentiment and investor sentiment. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1992M1-2015M12.

2.5 Conclusion

Despite the large literature on IPO, we still have relatively little understanding of why IPO hot and cold market phases exist. I provide an alternative explanation for the occurrence of IPO issue cycles by relating these cycles to time-varying economic uncertainty. Specifically, I empirically analyze the impact of recently developed measures of economic uncertainty on the number of IPOs, the number of newly filed IPOs and the number of withdrawn IPOs. The estimations reveal a robust and negative impact of uncertainty on IPO activity. For example, a one standard deviation increase in macroeconomic uncertainty decreases the number of IPOs by roughly four. Both the reduction of the number of newly filed IPOs and the increase of the number of withdrawn IPOs contribute to the lower IPO number. These findings suggest the existence of the real options effect of waiting in the IPO market during periods of high uncertainty. Moreover, I find that an increase in uncertainty is negatively related to the (future) IPO market condition variables which include the S&P 500 return, GDP growth, industrial production growth, investor optimism and consumer sentiment. The empirical results also identify macroeconomic uncertainty as the most crucial uncertainty driver of the IPO market. Since high uncertainty shocks are relatively persistent and take some time to fade away, they are likely to impede the IPO number for a considerable amount of periods, and as uncertainty eventually dissolves, IPO-interested firms start to go public in the same time slot. This mechanism helps to widen the understanding of why IPO issue cycles exist. Nevertheless, it would be interesting to see if the response to uncertainty shocks has sectoral variation. For example, firms in capital-intensive industries might be more cautious than IT-firms, which are more willing to go public as soon as possible to ensure the first-mover advantage in a fast-paced market.

Appendix

Data Appendix

- IPO data
  - Number of IPOs (IPO number): The number of IPOs per month are provided by Jay Ritter (https://site.warrington.ufl.edu/ritter/ipo-data/).
  - Initial returns (Underpricing): The initial returns represent the mean, across all IPOs each month, of the percentage difference between a closing price within the first month after the IPO and the offer price. A more complete description of the construction of the data is in Ibbotson et al. (1994). The data is provided by Jay Ritter (https://site.warrington.ufl.edu/ritter/ipo-data/).
  - Number of filed IPOs: The number of filed IPOs per month are fetched from the NASDAQ IPO database.
  - Number of withdrawn IPOs: The number of withdrawn IPOs per month are fetched from the NASDAQ IPO database.
- Uncertainty Measures
  - *Macro Uncertainty*: The macroeconomic uncertainty by Jurado et al. (2015) is collected from the website of Sydney Ludvigson (http://www.sydneyludvigson.com/data-and-appendixes/)
  - *Finance Uncertainty*: The financial uncertainty by Ludvigson et al. (2016) is collected from the website of Sydney Ludvigson (http://www.sydneyludvigson.com/data-and-appendixes/)
  - *Policy Uncertainty*: The economic policy uncertainty by Baker et al. (2016) is collected from http://www.policyuncertainty.com/
  - *VIX*: The VIX is collected from the Federal Reserve Bank of St.Louis (https://fred.stlouisfed.org).
- Other variables
  - The S&P 500, the industrial production index and the consumer confidence are collected from the Federal Reserve Bank of St.Louis (https://fred.stlouisfed.org).

- Monthly GDP: Monthly GDP is collected from the Macroeconomic Advisers database (http://www.macroadvisers.com/).
- Term spread: Term spread is collected from the Federal Reserve Bank of New York.
- Investor sentiment: I follow Han (2008) and proxy investor sentiment as the fraction of bullish investors minus the fraction of bearish investors. I use the database from the American Association of Individual Investors (http://www.aaii.com/) to calculate the investor sentiment for the benchmark estimation. As a robustness check, I use the database from Investors Intelligence (http://www.investorsintelligence.com/x/default.html) to compute the investor sentiment. The overall results are very similar.

Supportive Tables

Table 2.9: Time Series Analysis of IPO Number with Two Lags

Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Macro Uncertainty	-39.5***		-43.1***		-40.7***	
	(11.51)		(11.21)		(11.98)	
Control variables						
IPO number	.7182***	.7721***	.7295***	.7721***	.7230***	.8002***
	(.0564)	(.0598)	(.0588)	(.0598)	(.0592)	(.0556)
Underpricing	.0662**	.0485	.0807*	.0485	.0730	.0592
	(.0334)	(.0503)	(.0478)	(.0503)	(.0497)	(.0507)
Term structure	-.004	.6909	-.364	.6909	-.134	.6902
	(.5595)	(.6268)	(.5419)	(.6268)	(.5941)	(.5994)
SP 500 return	24.64	48.76	14.69	48.76		
	(24.83)	(30.01)	(25.50)	(30.01)		
Industrial production growth	-28.7	157.8	-42.4	157.8		
	(177.2)	(180.3)	(178.4)	(180.3)		
GDP growth	-315.	-246	-299.	-246		
	(202.4)	(199.7)	(192.1)	(199.7)		
Consumer sentiment	.0933	.1761**			.0271	.0995
	(.0851)	(.0859)			(.0807)	(.0786)
Investor sentiment	-2.56	-6.87			.7796	-1.01
	(6.935)	(7.362)			(5.713)	(5.838)
N	264	264	264	264	287	287
Adjusted R	.6347	.6206	.6386	.6206	.6343	.6173
Akaike Criterion	4.821	4.852	4.796	4.852	4.763	4.802
Schwarz Criterion	5.078	5.082	4.999	5.082	4.916	4.929

The table shows regressions in which the number of IPOs is the dependent variable. The first two lags of all explanatory variables are included in the estimation. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1992M1-2015M12, since the monthly GDP variables are not available prior to 1992. Regressions with a sample 1990M1-2015M12 without GDP growth deliver very similar results.

Table 2.10: Time Series Analysis of IPO Number with One Lag

Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Macro Uncertainty	-39.1***		-41.3***		-36.2***	
	(9.422)		(8.650)		(8.856)	
Control variables						
IPO number	.6915***	.7511***	.6976***	.7511***	.6849***	.7513***
	(.0490)	(.0520)	(.0501)	(.0520)	(.0520)	(.0501)
Underpricing	.0813**	.0708*	.0878**	.0708*	.0812**	.0726*
	(.0339)	(.0388)	(.0408)	(.0388)	(.0409)	(.0404)
Term structure	.2062	.7379	.0032	.7379	.1221	.6570
	(.5198)	(.5903)	(.4869)	(.5903)	(.5347)	(.5589)
SP 500 return	-4.86	8.706	-5.96	8.706		
	(20.54)	(21.52)	(19.62)	(21.52)		
Industrial production growth	-99.9	-17.0	-99.8	-17.0		
	(125.0)	(120.8)	(118.3)	(120.8)		
GDP growth	-208.	-210.*	-205.	-210.*		
	(129.3)	(123.3)	(121.4)	(123.3)		
Consumer sentiment	.0514	.1396*			.0229	.0986
	(.0762)	(.0758)			(.0713)	(.0687)
Investor sentiment	-.539	-2.29			1.454	.5530
	(5.600)	(6.055)			(4.530)	(4.607)
N	275	275	275	275	299	299
Adjusted R	.6352	.6186	.6373	.6186	.6361	.6213
Akaike Criterion	4.796	4.837	4.783	4.837	4.735	4.772
Schwarz Criterion	4.927	4.955	4.888	4.955	4.810	4.834

The table shows regressions in which the number of IPOs is the dependent variable. The first lag of all explanatory variables are included in the estimation. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1992M1-2015M12, since the monthly GDP variables are not available prior to 1992. Regressions with a sample 1990M1-2015M12 without GDP growth deliver very similar results.

Table 2.11: Time Series Analysis of IPO Number without Monthly GDP

Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Macro Uncertainty	-39.3***		-39.9***		-44.4***	
	(12.88)		(12.31)		(12.90)	
Control variables						
IPO number	.7873***	.7800***	.7852***	.8449***	.7797***	.8670***
	(.0549)	(.0583)	(.0598)	(.0564)	(.0591)	(.0542)
Underpricing	.0720**	.0466	.0735*	.0567	.0794*	.0657
	(.0322)	(.0510)	(.0423)	(.0477)	(.0463)	(.0488)
Term structure	.0577	.5691	.0124	.6412	-.294	.4756
	(.5874)	(.6398)	(.5215)	(.6113)	(.5850)	(.5898)
SP 500 return	91.97**	112.4***	81.08***	126.5***		
	(37.27)	(40.92)	(28.93)	(39.93)		
Industrial production growth	-133.	195.1	-157.	85.24		
	(207.2)	(213.8)	(212.6)	(206.6)		
Consumer sentiment	.0056	.1247			-.047	.0189
	(.0886)	(.0873)			(.0830)	(.0803)
Investor sentiment	-1.44	-6.12			4.643	3.478
	(7.487)	(7.631)			(6.545)	(6.704)
N	277	277	277	277	279	279
Adjusted R	.6603	.6144	.6650	.6410	.6616	.6371
Akaike Criterion	4.749	4.863	4.716	4.795	4.716	4.776
Schwarz Criterion	5.076	5.138	4.964	5.082	4.950	4.971

The table shows regressions in which the number of IPOs is the dependent variable. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1990M1-2015M12.

Table 2.12: Time Series Analysis of IPO Number without GDP 1980M1-2015M12

Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Macro Uncertainty	-20.2**		-16.4***		-24.6***	
	(7.991)		(5.983)		(7.684)	
Control variables						
IPO number	.7939***	.7546***	.8045***	.8091***	.8075***	.8432***
	(.0408)	(.0492)	(.0456)	(.0478)	(.0452)	(.046)
Underpricing	.0925***	.0735*	.0799**	.0797**	.1106***	.0933**
	(.0293)	(.0418)	(.0385)	(.0394)	(.0394)	(.0398)
Term structure	-.157	.2941	-.208	.2984	-.318	.3585
	(.3655)	(.3843)	(.3855)	(.3724)	(.4007)	(.3740)
SP 500 return	130.0***	132.2***	102.5***	140.0***		
	(31.69)	(34.34)	(24.83)	(33.53)		
Industrial production growth	46.48	241.8*	16.63	171.8		
	(144.8)	(137.5)	(147.1)	(133.9)		
Consumer sentiment	-.031	.0605			-.055	.0264
	(.0505)	(.0432)			(.0538)	(.0411)
Investor sentiment	-.062**	-.077**			-.010	-.002
	(.0288)	(.0322)			(.0297)	(.0281)
N	393	393	393	393	395	395
Adjusted R	.6631	.6326	.6647	.6508	.6547	.6399
Akaike Criterion	4.597	4.675	4.578	4.626	4.606	4.641
Schwarz Criterion	4.850	4.887	4.770	4.849	4.787	4.792

The table shows regressions in which the number of IPOs is the dependent variable. Robust standard errors are in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level. The sample is 1980-2015M12. The investor sentiment is calculated from the Investors Intelligence database.

CHAPTER 3

Real Options Effect of Uncertainty and Labor Demand Shocks on the Housing Market

This chapter is joint work with Gabriel Lee and Johannes Strobel.

Abstract: This paper documents that macroeconomic uncertainty affects the housing market in two significant ways. First, uncertainty shocks adversely affect housing prices but not the quantities that are traded. Controlling for a broad set of variables in fixed-effects regressions, we find that uncertainty shocks reduce housing prices and median sales prices in the amount of 1.4% and 1.8%, respectively, but the effect is not statistically significant for the percentage changes of all homes sold. Second, when both uncertainty and local demand shocks are introduced, the effects of uncertainty on the housing market dominate that of local labor demand shocks on housing prices, median sell prices, the share of houses selling for loss, and transactions. The aforementioned effects are largest for the states that exhibit relatively high housing price volatilities, suggesting real options effects in the housing market during the times of high uncertainty.

3.1 Introduction

Three well documented features of the recent Great Recession are the decline in housing prices, the increase in unemployment rate, and the increase in the presence of uncertainty in the United States. Figure 3.1 shows the correlation between the U.S. housing price growth rate and some of the uncertainty measures in the recent literature over the period from 1990 to 2014 with the highlighted recession periods: a clear negative correlation between the housing price growth rate and the shown uncertainty measures.[1]

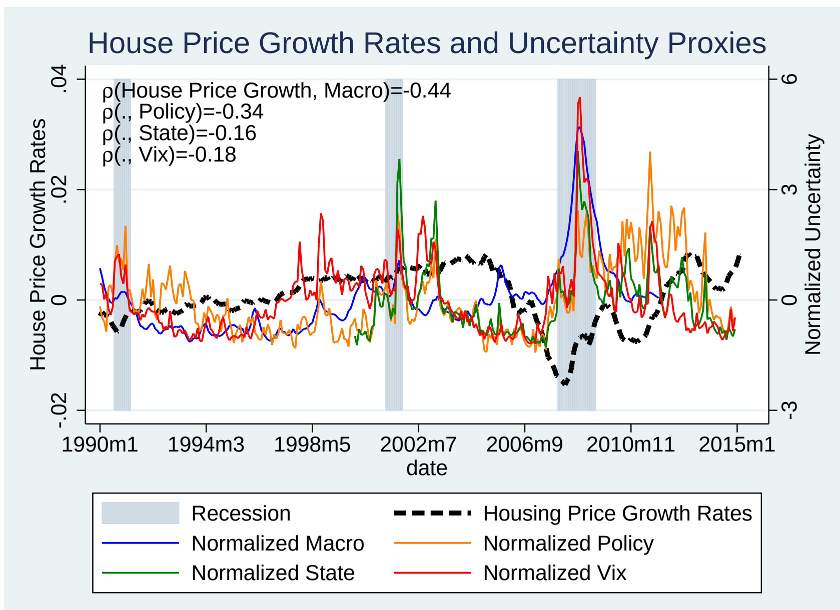

Figure 3.1: House Price Growth Rates and Uncertainty Proxies

Time series of the house price growth rates and the four uncertainty measures, 1990M1-2014M12. The shaded areas denote the periods of recession according to the NBER definition.

[1]We use four different uncertainty measures in our analysis: the *Macro Uncertainty* by Jurado et al. (2015), the *VIX* by Bloom (2009), the *Policy Uncertainty* by Baker et al. (2016), and our measure, which is analogous to Baker et al. (2016) but on a state level (*State Uncertainty*). Correlations between these uncertainty measure over these periods range between 0.25 and 0.63.

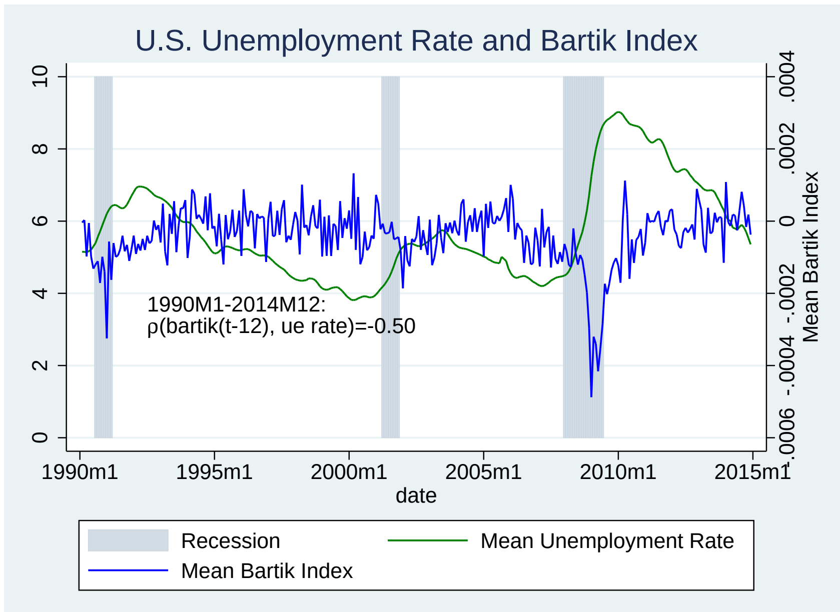

Figure 3.2: Unemployment Rate and Labor Demand Shocks

Time series of the unemployment rate and Bartik index which captures labor demand shocks, 1990M1-2014M12. The shaded areas denote the periods of recession according to the NBER definition.

Figure 3.2 also shows a strong negative correlation between the monthly U.S. unemployment rate and the Bartik index that proxies the U.S. labor demand shocks from 1990M1 to 2014M12.

There are numerous recent papers that deal with the effects of uncertainty and labor demand shocks on aggregate economy as well as housing and labor markets separately. For example, Christiano et al. (2014) show that uncertainty adversely impacts the economy, while Dorofeenko et al. (2014) show uncertainty shock can explain the U.S. housing price volatilities. For the labor demand shock on housing and labor markets, Edlund et al. (2015) examine the impact of labor demand shocks, using the Bartik index, on housing prices, and Shoag and Veuger (2014) empirically show that uncertainty may amplify labor demand shocks. This paper, however, examines the simultaneous effects of uncertainty and local labor demand shocks on the U.S. housing market. We specifically look at the average housing prices, the median selling prices, the share of houses selling for loss and transactions (houses sold). More precisely, we seek to answer (i) does uncertainty directly affect the housing market, (ii) if a local labor demand shock occurs in a period of high uncertainty, is the impact different compared to a period of low uncertainty and (iii) how robust are the outcomes given the choice of the uncertainty proxy and the threshold level defining a period of high uncertainty?

First, controlling for a broad set of variables, we find that uncertainty shocks directly affect prices but not quantities. The median sell price as well as the housing price decrease on average by 1.80% and 1.42%, respectively. Second, a positive local labor demand shock significantly increases median sell prices, house prices and transactions and decreases the share of houses selling for loss. If a labor demand shock occurs during a period of high uncertainty, however, then it essentially affects neither prices nor quantities: Home sellers and -buyers do not trade at the price and wait out in selling and buying until the uncertainty periods are over. This observation is consistent with the occurrence of a real options effect akin to the irreversibility of an investment described by Pindyck (1991, p.1117): "There will be a value to waiting (i.e., an opportunity cost to investing today rather than waiting for information to arrive) whenever the investment is irreversible and the net payoff from the investment evolves stochastically over time". For instance, Bloom et al. (2007) show that because of real options effects, firms' responsiveness to demand shocks is generally lower in periods of high uncertainty. Capozza and Helsley (1990) are the first to examine the impact of uncertainty on land values and development decisions in a spatial context. Geltner et al. (1996) show that alternative uses lead to a delay in development, while Childs et al. (1996) demonstrate that the ability to mix uses and to redevelop affects the timing of land development. Holland et al. (2000), Childs et al. (2002), Clapp et al. (2013), Bulan et al. (2009), and Cunningham (2006, 2007) empirically show that real options play an important role for house prices dynamics, housing investment and land prices.

Analogous to the irreversible investment literature, we find the response of housing market variables to labor demand shocks to be much lower in times of high uncertainty, suggesting real options effects (option to "wait and see") in the housing market during times of high uncertainty. More specifically, we show that following an adverse shock in labor demand of one standard deviation, the real option value ("wait and see" effect) in the housing price amounts to 0.19%, and the effect increases to 0.32% for the states (locations) that exhibit relatively high housing price volatilities. Furthermore, we find that following an adverse labor demand shock, not only the share of houses selling for loss significantly decreases in times of high uncertainty when compared to normal times, but also the number of homes sold remains almost constant.[2] To show that the real option value increases with higher uncertainty, we sort the fifty one states into three equal-sized groups, according to the unconditional housing price volatility in each state. In doing so, we find that while the impact of local labor demand shocks is largest for the group with the highest housing price volatility, uncertainty completely offsets the labor demand shock - as opposed to the other two groups, where we find no significant impact of uncertainty.

Our results, thus, indicate uncertainty shocks affect housing price movements both directly and indirectly. On the one hand, uncertainty adversely affects housing prices. On the other hand, it alters the impact of shocks during uncertain times, with this latter effect consistent with the presence of real option effects arising in a period of high uncertainty in the housing market.[3] One important implication of our results, analogous to Bloom et al. (2007), is that in order for policy measures to work properly, highest priority should be given to the reduction of uncertainty.[4]

We address real option issues in housing markets using monthly U.S. state-level data from 1990 to 2014. We construct binary uncertainty dummies to indicate the periods of high uncertainty, as in Bloom (2009) and a variation of the Bartik index proposed by Bartik (1991) as local labor demand shocks to quantify the impact of these two shocks on the housing market. Our approach thus corresponds to models using two-state Markov-switching processes, where regime changes can be documented by an uncertainty index crossing various threshold values, which are based on the percentiles of the distribution of the uncertainty proxy. Our approach in defining the threshold values differs from the one used in, for example, Bloom (2009), who defines periods of uncertainty as the proxy when 1.65 or more standard deviations above the mean. We use the macroeconomic uncertainty measure by Jurado

[2]We show the robustness of the above results to different threshold values that are ranged from 80th, 85th, 90th and 95th percentile of an uncertainty proxy.

[3]See also Aastveit et al. (2013), in which structural Vector Autoregressions are used to document wait-and-see effects in monetary policy during periods of high uncertainty. See also Bloom (2014) for further discussion and sectors where real option effects arise.

[4]Especially in light of the results of Stroebel and Vavra (2014), who show that there is a causal relation between changes in housing prices and changes in retails prices and thus consumption.

et al. (2015) as our benchmark measure but we also include other uncertainty measures such as the economic policy uncertainty proxy by Baker et al. (2016), the *VIX* which is also used by Bloom (2009), and the state-level uncertainty similar to Baker et al. (2016) to analyze the state level housing markets.

3.2 Data, Bartik Index and Uncertainty Measures

In the following section, we describe the data as well as the construction of the Bartik index and various uncertainty measures used in our empirical analysis.

3.2.1 Data

We use monthly state-level data from 1990M1 to 2014M12; the data and sources are described in detail in the Appendix. Zillow Real Estate Research data and Freddie Mac provide information on various aspects of the housing market, such as the housing price, median sales price, the share of houses sold for loss and turnover. The housing price is the inflation adjusted housing price index from Freddie Mac; the median sales price is defined as the median of the selling price for all homes sold in a given state. The share of houses sold for loss is defined as the percentage of homes in an area that sold for a price lower than the previous sale price and turnover is defined as the percentage of all homes in a given area that are sold in the past 12 months. These housing variables constitute the vector of dependent variables.

3.2.2 Bartik Index

The Bartik index is a measure of the predicted change in demand for employment in a state given by the interaction between a state's initial industry mix and national changes in industry employment. The index compares the preexisting differences in the sectoral composition of employment across states with the broad changes in national employment, especially changes subject to a trend, asymmetrically impact states. In this paper, we follow Saks (2008) to construct the Bartik index. We use the index of Saks (2008) due to its transparency and straightforward interpretation:

$$bartik_{it} = \sum_j \frac{e_{ijt-1}}{e_{it-1}} \left(\frac{\tilde{e}_{ijt} - \tilde{e}_{ijt-1}}{\tilde{e}_{ijt-1}} - \frac{e_t - e_{t-1}}{e_{t-1}} \right) \tag{3.1}$$

where i=state, j=industry, t=month; $\tilde{e}_{ijt}$ = national industry employment outside of state i; e_{it}= state employment = $\sum_j e_{ijt}$; e_t= national employment = $\sum_i e_{it}$; e_{ijt} = employment in state i in industry j.

The first fraction reflects the share of industry j employment relative to the total employment in state i in $t-1$, the second fraction is the growth rate of industry j outside of state i and the third fraction reflects the change in national employment. Thus, the term in brackets reflects the change in industry j employment (outside state i) relative to changes in national employment. This term is weighted by the "importance" of industry j in state i in $t-1$. We use j=4 sectors across i=51 states in this analysis: manufacturing, private services, public services and construction and logging. We use the time series of the Bartik index aggregated across states as displayed in Figure 3.2. The results remain unchanged if we exclude the construction sector from the Bartik index.

3.2.3 Uncertainty Measures

Various uncertainty proxies have been proposed in the recent literature. As shown in Figure 3.1, depending on the preferred proxy, the number of uncertainty shocks may differ considerably, although it is also possible that different proxies capture different aspects of uncertainty. We use the *Macro Uncertainty* measure, due to Jurado et al. (2015), for our baseline results because it is, by construction, uncorrelated with any single time series. *Macro Uncertainty* captures the predictability of the overall macroeconomic environment; the less predictable the macroeconomic variables, the higher the macroeconomic uncertainty. We decided to use the one-month-ahead measure, since the data are at a monthly frequency. See section 1.2 for a more detailed description of the data.

We also use three uncertainty measures including *Policy Uncertainty*, the *VIX* and *State Uncertainty* for the robustness check on our empirical analysis. The *State Uncertainty* indicator is constructed as the monthly number of news-paper articles in a state containing either one of the keywords "economic uncertainty", "economy uncertain" or "economy uncertainty" from 2000M1 until 2014M12[5]. We also scale the *State Uncertainty* indicator by the number of newspapers and normalize it by dividing by the standard deviation in each state in a robustness check of the estimation results. In creating this index, we follow Baker et al. (2016). As can be seen in Figure 3.1, there are considerable differences in fluctuations, and thus in the periods classified as uncertain.[6] A definition of the threshold value is needed in order to identify the number of uncertainty periods and to construct binary uncertainty series. Bloom (2009) suggests using "1.65 standard deviations above the mean, selected as the 5% one-tailed significance level treating each month as an independent observation". However, specifying the threshold in this manner does not leave any adjustment opportunity if the assumption of Normality and independently and identically distributed uncertainty shocks does not hold.[7] Table 3.1 shows the number of months defined as "uncertain" by various uncertain proxies. For example, using the *Macro Uncertainty* by Jurado et al. (2015), when α equals 5% then the Normal Distributional assumption leads to seventy-six uncertain periods instead of fifty-eight periods when one uses the corresponding percentiles of the actual distribution. Consequently, we use the corresponding percentiles at various levels in our analysis to show the robustness of empirical results as well as to avoid the Normal i.i.d. assumption. Figure 3.3 shows the time periods defined as uncertain using different uncertainty proxies. The right-lower panel also displays the state uncertainty proxy after aggregating, although there is substantial variation across states. Note, however, the similarities between the economic policy uncertainty indicator and our *State Uncertainty* proxy.

[5] The data on state-level news-paper articles are collected from www.newslibrary.com.

[6] See Strobel (2015) for further elaboration on the reasons for this observation.

[7] We tested for the normality of the uncertainty proxies using the Jarque-Bera test, and the null of normality was rejected for each proxy.

Table 3.1: Number of Months Defined as Uncertain.

	20 %		15%		10%		5%	
	$1-\alpha$	α	$1-\alpha$	α	$1-\alpha$	α	$1-\alpha$	α
	Percentile (P)	Normal (N)	P	N	P	N	P	N
Macro Uncertainty	124	104	103	96	80	86	58	76
Policy Uncertainty	192	188	174	175	156	162	138	148
State Uncertainty	36	27	27	21	18	18	9	13
VIX	240	222	225	217	210	206	195	197

Note: Number of months defined as uncertain from 1960:1 - 2011:12 for *Macro Uncertainty*, 1985:1 - 2015:2 for *Policy Uncertainty*, 2000:1 -2014:12 for *State Uncertainty* and 1990:1 - 2015:2 for the *VIX*; the α one-tailed significance level is from the Normal Distribution and the series assume to follow i.i.d. as in Bloom (2009).

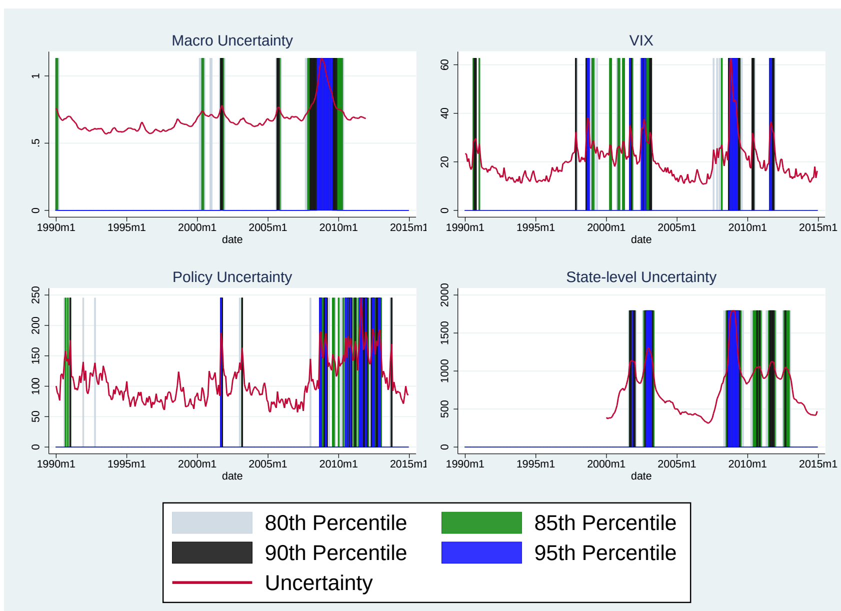

Figure 3.3: Periods of High Uncertainty

Time series of the unceraintу measures and the corresponding periods whichs are defined as highly uncertain, 1990M1-2014M12. The shaded areas denote the periods in which the uncertainty measures exceed their corresponding 80-th, 85-th, 90-th and 95-th percentile, respectively. Exceeding, for example, the 80-th percentile means that the respective uncertainty measure is greater than 80% of its values in the sample.

3.3 Estimation Methodology and Results

3.3.1 Estimation Methodology

As we seek to investigate the role of uncertainty in the housing market, we interact uncertainty and labor demand shocks. To address various econometric issues in our emprical setup, we first use the standard errors developed in Driscoll and Kraay (1998) to account for spatial dependence, heterogeneity and autocorrelation. To guard against feedback effects, we lag the explanatory variables. Moreover, by construction, our uncertainty measure are exogenous. For example, our benchmark *Macro Uncertainty* measure, as stated above, consists of purely unforecastable components. Consequently, by the definition and construction of the *Macro Uncertainty*, there should not be any underlying simultaneity between housing market variables and the *Macro Uncertainty*. Moreover, the *VIX*, which captures the expected volatility of the S&P 500 index, is also unlikely to be strongly influenced by housing prices. And, although, *Policy Uncertainty* and the *State Uncertainty* measure might be affected in the same period news, it seems rather unlikely that housing prices today affect yesterday's news coverage. Additionally, we include a rich set of controls to avoid an omitted variable bias.[8] As for the Bartik index, the local labor demand shocks $bartik_{it}$ are constructed to be exogenous given a constant labor supply. Binary uncertainty indicators are coded to be one if uncertainty is above a threshold value and zero otherwise.

Our empirical model is given by:

$$y_{it} = x_{it-\tau}\vec{\gamma} + 1_{unc,it-\tau}\vec{\beta}_{1t-\tau} + bartik_{it-\tau}\vec{\beta}_{2t-\tau} + 1_{unc,it-\tau} \times bartik_{it-\tau}\vec{\beta}_{3t-\tau} + \alpha_i + u_{it} \tag{3.2}$$

where $x_{it-\tau}$ is a vector containing up to τ lags of the control variables, γ is the corresponding parameter vector, α_i is the state specific intercept, $1_{unc,it-\tau}$ and $bartik_{it-\tau}$ are $(1 \times \tau)$ vectors of lagged uncertainty indicators and labor demand shocks, respectively, and $\beta_{jt-\tau}$, $j = 1,2,3$ are the corresponding $(\tau \times 1)$ parameter vectors. An element of $\beta_{jt-\tau}$ reflects the impact of the respective lag, while the sum of the elements gives the long-run impact. We experimented with different lag-lengths and use $\tau = 6$ lags as baseline specification,

[8] In particular, due to the long time dimension, we cannot use time fixed-effects in this setting. Therefore, we include a host of controls in order to capture variation in the economic environment. The complete set of control variables used for our empirical analysis is shown in the Appendix.

but the results are not sensitive to the number of lags as long as we use more than two and less than seven. The coefficients of main interest are $\beta_{1t-\tau}$, $\beta_{2t-\tau}$ and $\beta_{3t-\tau}$. $\beta_{1t-\tau}$ reflects the impact of a regime-change from low to high uncertainty, $\beta_{2t-\tau}$ reflects the impact of a local labor demand shock on the housing market and $\beta_{3t-\tau}$ states the (change in the) effect of a local labor demand shock in a period of high uncertainty. In other words, $\beta_{3t-\tau}$ is a measure for the change in the responsiveness of the housing market variables due to high uncertainty. If $\beta_{3t-\tau}$ is significantly different from zero and its sign is different (same) from $\beta_{2t-\tau}$, then uncertainty diminishes (amplifies) the impact of the local labor demand shock.

For example, in an uncertain period, even though the impact of an adverse labor demand shock on the housing price is negative, home sellers will most likely not sell at the lower prices as this would unnecessarily reduce the return of the most important asset of most households. The underlying assumption is that the investment opportunity (selling or buying the house) is irreversible once exercised but available until then. In that sense, $\beta_{3t-\tau}$ proxies the real option value by capturing the change in the equilibrium housing price or the median selling price that does not materialize following a labor demand shock because of uncertainty.

3.3.2 Baseline Results

Our empirical objectives are to show (i) the quantitative effect of uncertainty on the housing market, (ii) the change in the impact of local labor demand shocks on the housing market if they occur during periods of uncertainty and (iii) the sensitivity of the results with respect to varying threshold levels and different uncertainty proxies. Table 3.2 shows occurrence of the diminished responsiveness due to uncertainty in our benchmark regression results, based on the *Macro Uncertainty* measure, $\mathbf{1}_{macro}$. The estimated $\vec{\beta}_j$ represent the long-run effect, i.e. the sum of the estimated elements of $\vec{\beta}_{jt-\tau}$.[9]

The second column of Table 3.2 shows the long-run impact, $\vec{\beta}_1$, of uncertainty on housing prices, median sell prices, the percentage loss of houses selling and turnover; we control for the federal funds rate, housing starts proxying for residential investment, income, industrial production, inflation,

[9] We use 95th percentile as our cut off point for the *Macro Uncertainty* measure.

Table 3.2: Long-run Effects of Uncertainty, Bartik and Interaction Term

Dependent Variable	$\mathbf{1}_{macro}$	Bartik	Bartik*$\mathbf{1}_{macro}$	*Obs.*
Δlog(median sales price)	-.0180**	32.63***	-31.68***	6,539
	(.00752)	(10.679)	(11.765)	
Δlog(house price)	-.0142***	10.93***	-14.35***	13,158
	(.00344)	(3.8337)	(4.3892)	
Δ% selling for loss	.52575	-1133.00**	994.94**	5,904
	(.37032)	(492.26)	(485.88)	
Δturnover	-.0036	147.26**	-202.00**	6,011
	(.05451)	(66.317)	(79.781)	

Note: Sample period from 1990 onwards. The long-run effects of uncertainty (95th percentile threshold), bartik and interaction term are presented with corresponding standard errors in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

population, and the S&P 500 and the unemployment rate.[10] As opposed to the predictions by Dorofeenko et al. (2014)[11], we find that uncertainty adversely affects the median sell prices and house prices on average by 1.80% and 1.42%, respectively. In other words, Dorofeenko et al. (2014) results are driven by the supply side, which our empirical results do not necessarily support. Moreover, we find uncertainty impacts neither turnover nor the share of houses selling for loss directly. The intuition for this findings is that in the long-run uncertainty decreases, on average, buyers' willingness to pay. Because sellers do not want to postpone selling indefinitely, they reduce the asking price, which in turn reduces the equilibrium housing price.

For the robustness check on the uncertainty measures, we also show the results for different threshold values (i.e. percentile cutoffs) as shown in

[10]We include these variables to capture the demand and supply factors that influence the local housing market and the information available to market participants (i.e. robustness checks for endogeneity and omitted variables). We also check for various Granger causality test. We conduct other variety of robustness checks described in the next subsection.

[11]Dorofeenko et al. (2014) show that an increase in their measure of uncertainty has an increasing effect on house prices due to the default premium on the housing developers: There is a markup on housing prices due to the bankruptcy possibility that is caused by uncertainty.

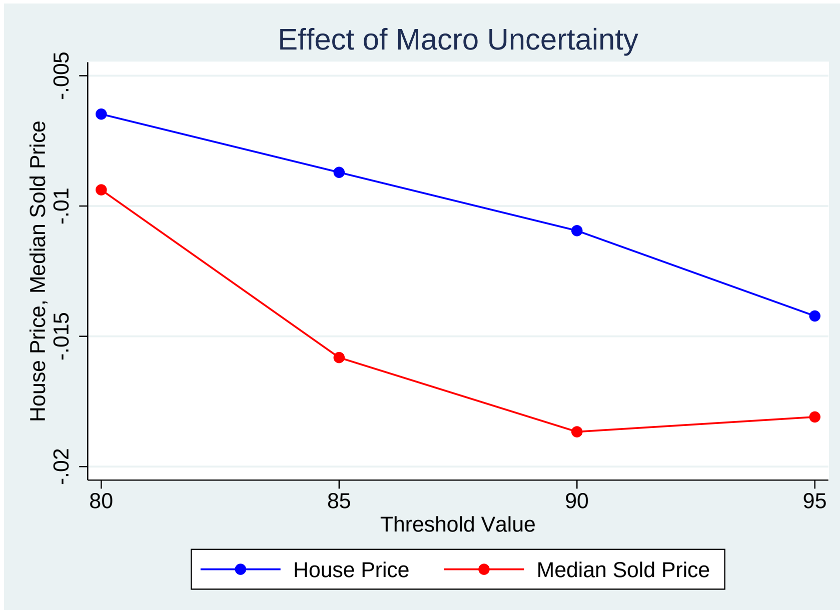

Figure 3.4: The Impact of *Macro Uncertainty*

The graph illustrates the long-run impact of *Macro Uncertainty* on the house price and the median sold price for the different threshold values which are used to identify periods of high uncertainty.

Figure 3.4. Regardless of the threshold value, the sign and the significance of the estimated $\vec{\beta}_1$ for the log house price and log median sales price do not change.[12]

The column three of Table 3.2 shows the long-run impact of labor demand shocks, proxied by $bartik$. The impact is highly significant for all dependent variables, even after controlling for state-level unemployment. For example, one standard deviation increase in the local labor demand shock (i.e., the $bartik$, which is defined as change in state-level employment relative to a change in national employment), increases house prices, median sell prices and transactions on average by .14%, .43% and 1.92%-points, respectively and decreases the share of houses selling for loss by 14.77%-points. Due to linearity, the signs reverse in the case of adverse labor demand shocks - as

[12] All of the coefficients are significant at a 1% significance level, except for one which is significant at the 5% level.

observed in most states during the Great Recession period.[13]

The above results indicate that the uncertainty and labor demand shocks affect the housing market variables in opposite direction. To determine the quantitative effects of these two shocks on the housing variables, we introduce an interaction term, $\vec{\beta}_3$: the results are shown in the fourth column of Table 3.2. When the labor demand shock occurs during a period of high uncertainty then, for almost every dependent variable and threshold level, the effect of uncertainty shock dominates the labor demand shock: a clear sign change from the estimated $\vec{\beta}_2$ being positive to the estimated $\vec{\beta}_3$ being negative.

As discussed above, $\vec{\beta}_3$ quantifies the homeowners' diminished response ("wait and see effect") following a labor demand shock: 0.19% (0.013% × 14.35) of the house price and 0.41% (0.013% × 31.68) of the median sell price. For the expositional purpose of the interaction term, Figure 3.5 shows the effects of a labor demand shock with - and without uncertainty shock (using our benchmark *Macro Uncertainty* shock). All dots in the graphs are significant at the 10% significance level. The blue line (Bartik Normal Times) summarizes the long-run impact of labor demand shocks, $\vec{\beta}_2$, on the various dependent variables, while the red line (Bartik High Uncertainty) represents the impact of labor demand shocks in uncertainty times, i.e. $\vec{\beta}_2 + \vec{\beta}_3$. Figure 3.5 clearly shows that when uncertain periods occur then the effect of the labor demand shock is greatly muted. These dominating uncertainty shock effects suggest the presence of real options effects in housing market. This result is in line with the findings of Quintin and Davis (2014), who find that uncertainty about housing prices kept the default rate low relative to a situation without uncertainty. Figure 3.6 is analogous to Figure 3.5, but with *State Uncertainty* shock: the results are not overturned.

[13]We report the impact of a standard deviation increase due to the scale of the *bartik*. Mean local labor demand decreases from 1990 until 2014 by 0.004%-points, while one standard deviation corresponds to 0.013%-points: For example, for the log house price, we report an increase of 0.14% as 0.013 × 10.93, while the real option value is calculated similarly as 0.013 × 14.35 = 0.19%, where $\vec{\beta}_3 = 14.35$.

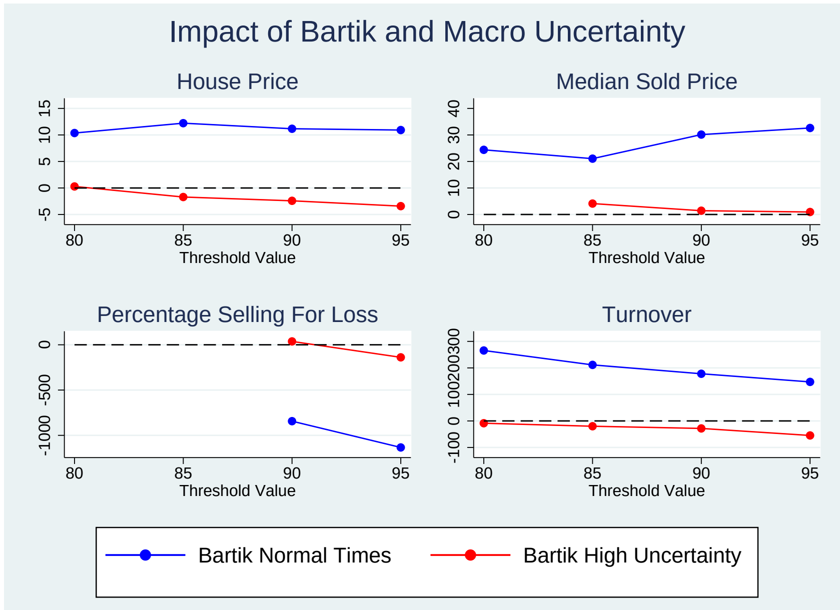

Figure 3.5: The Impact of Bartik and *Macro Uncertainty*

The graph illustrates the long-run impact of the Bartik index in periods of low and high *Macro Uncertainty* for the different threshold values which are used to identify periods of high uncertainty.

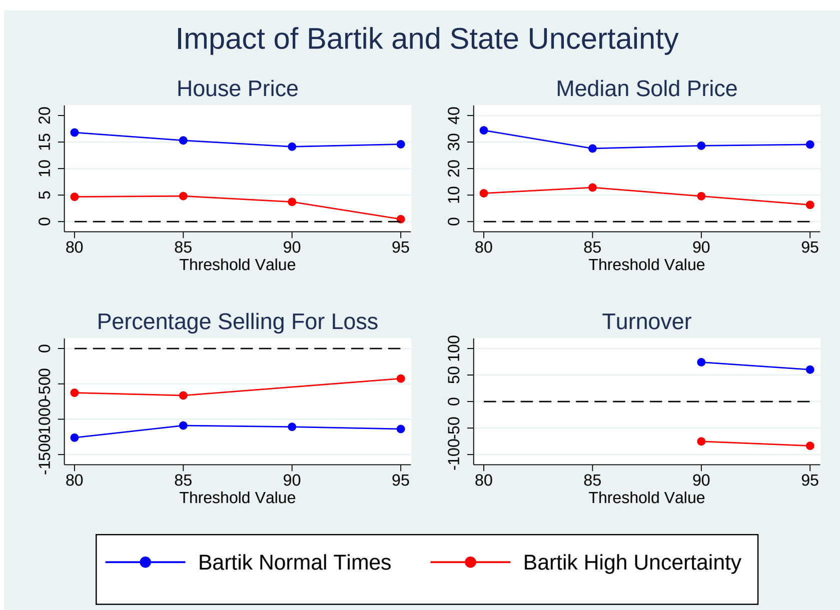

Figure 3.6: The Impact of Bartik and *State Uncertainty*

The graph illustrates the long-run impact of the Bartik index in periods of low and high *State Uncertainty* for the different threshold values which are used to identify periods of high uncertainty.

Table 3.3: Long-run Effects of Uncertainty, Bartik and Interaction Term: Other Uncertainty Measures

Dep. Variable	1_{macro}	Bartik (B)	B^*1_{macro}	1_{State}	B	B^*1_{State}	1_{vix}	B	B^*1_{vix}
$\Delta_{log(med\ sell\ price)}$	-.0180**	32.627***	-31.68***	-.0033	30.296***	-24.84**	-.0058	42.316***	-44.64***
	(.00752)	(10.679)	(11.765)	(.00405)	(11.723)	(12.330)	(.00930)	(12.339)	(16.513)
$\Delta_{log(house\ price)}$	-.0142***	10.925***	-14.35***	-.0048***	15.315***	-17.63***	.00191	12.625***	-11.40
	(.00344)	(3.8337)	(4.3892)	(.00144)	(4.2199)	(4.4932)	(.00482)	(4.2128)	(7.1745)
$\Delta\%$ selling for loss	.52575	-1133.**	994.94**	.48216**	-1229.**	1038.6*	.48033	-1584.0***	1517.5**
	(.37032)	(492.26)	(485.88)	(.23001)	(479.62)	(558.01)	(.54268)	(524.17)	(699.86)
$\Delta_{turnover}$	-.0036	147.26**	-202.0**	-.0577***	81.225*	-152.3***	.05951*	95.007*	-102.4
	(.05451)	(66.317)	(79.781)	(.02065)	(43.376)	(57.010)	(.03517)	(54.964)	(98.765)

Note: As the months defined as high uncertainty differ across the proxies, the variation used to identify $\vec{\beta}_{1t-\tau}$ and $\vec{\beta}_{3t-\tau}$, the coefficients of uncertainty and the interaction term, differs as well. The long-run effects of uncertainty (95th percentile threshold), bartik and interaction term are presented with corresponding standard errors in brackets. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

Overall, we find that the results in Bloom et al. (2007) for the firm level carry over to the housing market: uncertainty greatly diminishes the responsiveness of housing market variables to labor demand shocks. We note, however, our results are somewhat sensitive to the choice of the uncertainty proxy, which can be seen in Table 3.3. For example, the impact of uncertainty shocks on the growth rates of housing prices, median sell prices is robust although slightly differs quantitatively.

One exception is when the VIX is used to define periods of high uncertainty. This result is to be expected as the different uncertainty proxies indicate different periods of high uncertainty. Although we do not show the results with the *Policy Uncertainty* shock in Table 3.3, the real options effects ($\vec{\beta}_3$) from the *Policy Uncertainty* are not as strongly associated if high threshold values (90th or 95th percentile) are used. The reason might be that when the 95th percentile threshold, the *Policy Uncertainty* proxy represents only the periods that are associated with the post 2011 period (this includles the period during the European Debt crisis). And hence, there is not enough sample size to test for the interaction terms. However, if the 85th percentile is taken as threshold value, the interaction effects become significant again, as more periods, especially the months before 2010, are classified as periods of high uncertainty.

3.3.3 Grouping States by Housing Price Volatility

To analyze whether the real option effect varies by regions, we sort the fifty one U.S. states into three groups according to the unconditional housing price volatility in each state over time, and we estimate our model (3.2) for each one of the groups. The three groups are equal size and we refer to them as *low*, *medium* and *high*: Our hypothesis is to test empirically whether the change in the responsiveness of housing market variables is larger in the states with higher housing price volatilities compared to the lower housing price volatilities states. Consequently, we focus on the dominant effect of uncertainty over the labor demand shocks for each one of the groups, using the 95th percentile of the *State Uncertainty* proxy. We choose the *State Uncertainty* measure because we group the states according to the state-specific housing price volatility; the results are qualitatively similar, however, for the *Macro Uncertainty* measure. Table 3.4 shows the results for the three different groups.

Table 3.4: Long-run Effects of Bartik and Interaction Term Grouped by the Magnitude of the Housing Price Volatility Over Time

Housing Price Volatility	low		medium		high	
	Bartik (B)	$B{*}1^{low}_{state}$	B	$B{*}1^{medium}_{state}$	B	$B{*}1^{high}_{state}$
Δlog(house price)	18.47**	-6.85	7.055***	-9.26	21.26***	-25.0***
	(7.802)	(7.131)	(2.596)	(6.253)	(6.899)	(8.905)

Note: The long-run effects of bartik and interaction term based on *State Uncertainty* (95th percentile threshold) are presented with corresponding standard errors in brackets grouped by housing price volatility across states. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

The most striking difference between the three groups is with respect to the significance and the magnitude of our responsiveness measure ($\vec{\beta}_3$) for the *high* group. As one moves away from the low to high volatility group, the interaction term ($\vec{\beta}_3$) not only increases in absolute magnitude from -6.85 to -25 but also becomes highly statistically significant. That is, the effect of a one standard deviation increase (i.e. 0.013%−points) in the interaction term changes from $-6.85 \times 0.013 = 0.09\%$ in the *low* group to $-25.0 \times 0.013 = 0.32\%$ of the housing price in the *high* group.

3.3.4 Grouping States by the Impact of Local Labor Demand Shocks

For the robustness check, we also sort groups by the impact of local labor demand shocks. We calculate the impact of the *bartik* based on our model (3.2) with housing prices as dependent variable, but estimating time-series regressions for each state. We include states where the *bartik* has a significant impact (5% level) on the change in log housing prices, which results in 37 states. We sort these 37 states into three groups of almost equal size, depending on the magnitude of the *bartik*'s impact. Table 3.5 shows the long-run effects of the *bartik* and the interaction term. By construction, the impact of the *bartik* increases and is highly significant. The interaction term, however, is only statistically significant for the group *high,* with the sum of $\widehat{\vec{\beta}}_2$ and $\widehat{\vec{\beta}}_3$ ($e.g.$ $104.9 - 102 = 2.9$) very close to zero: the net effect on the change in log housing prices is almost zero. Moreover, an explanation for the dominance of uncertainty over the shock for the *high* group, in contrast to the *medium* and *low* group, is that the larger the impact of the shock, the less responsive households are, ceteris paribus.

Table 3.5: Long-run Effects of Bartik and Interaction Term Grouped by the Impact of the Bartik in Each State

Bartik Index	low		medium		high	
	Bartik (B)	$B{*}1^{low}_{State}$	B	$B{*}1^{medium}_{State}$	B	$B{*}1^{high}_{State}$
Δlog(house price)	9.835***	-5.16	52.98***	-16.1	104.9***	-102**
	(2.328)	(5.947)	(9.703)	(14.43)	(21.13)	(45.07)

Note: The long-run effects of bartik and interaction term based on *State Uncertainty* (95th percentile threshold) are presented with corresponding standard errors in brackets grouped by housing price volatility across States. * indicates significance at 10% level, ** indicates significance at 5% level, *** indicates significance at 1% level.

3.3.5 Robustness Checks

Our empirical results are robust to a variety of alternative specifications, such as including a recession dummy, using different lag lengths, constructing the Bartik index following Charles et al. (2013), scaling *State Uncertainty* by the number of newspapers and normalizing it by dividing by the standard deviation in each state, or omitting some of the variables from the vector of controls variables.[14] However, the results are not robust to omitting the Great Recession period, i.e. using the sample from 1990M1 until 2007M12. This may not be too surprising in light of Figure 3.3, which shows a lot of the variation in the uncertainty dummy comes from the differences between the time before and after 2008.

3.4 Conclusion

Our empirical results lend support for the real option effects in the U.S. housing market and are in line with some of the predictions of the theoretical model of Bloom et al. (2007). Using the state-level panel data from 1990M1 to 2014M12, we show (i) uncertainty has a small but highly significant impact on the level of housing prices but not on quantities, (ii) uncertainty dominates the effects of (adverse) labor demand shocks and (iii) the results are robust to changes in the threshold defining times of high uncertainty but are somewhat sensitive to the choice of uncertainty proxy. We interpret this result as the different proxies capturing different aspects of uncertainty, with the proxy of Jurado et al. (2015) being well suited, due to its construction, to capture the spells of uncertainty that induce macro-level real options effects. These findings might be helpful for housing policy makers to mitigate adverse effects of real shocks on housing markets during periods of high uncertainty before they materialize.

[14]The robustness checks are available from the authors on request.

Appendix

Data Appendix

Table 3.6: Uncertainty Proxies

Variable	Availability	Source	Regional level
Macro Uncertainty	1960M1-2011M12	Jurado et al. (2015)	National
Policy Uncertainty	1985M1-2015M2	Baker et al. (2016)	National
State Uncertainty	2000M1-2014M12	Self constructed	State
VIX	1990M1-2015M2	FRED	National

Table 3.7: Dependent Variables

Variable	Availability	Source	Regional level
House Price	1975M1-2014M12	Freddie&Mac	State
Median Sales Price	1996M4-2014M12	Zillow Database	State
% Selling For Loss	1998M1-2014M12	Zillow Database	State
Total Turnover	1998M1-2014M12	Zillow Database	State

Table 3.8: Control Variables

Variable	Availability	Source	Regional level
Federal Funds Rate	1954M7-2015M1	FRED	State
Housing Starts	1988M1-2015M1	FRED	State
Income	1950Q1-2014Q3	BEA	State
Industrial Production	1919M1-2015M1	FRED	National
Inflation Rate	1947M1-2015M1	FRED	National
Population	1972-2013	FRED	State
S&P 500	1970M1-2015M3	Datastream	National
Unemployment Rate	1976M1-2014M12	FRED	State

Table 3.9: Descriptive Statistics of the Housing Market Variables.

	Obs.	Mean	Std. Dev.	Min	Max
house price	24480	125.5488	25.6362	61.0220	275.6024
Δlog(house price)	24429	0.0002795	0.0073951	-0.1098976	0.0773649
Median Sales Price	7790	191184.8	74180.34	47519.08	518470.1
Δlog(Median Sales Price)	7751	0.001178	0.025107	-0.256864	0.308221
% Selling For Loss	7234	12.8908	13.5806	0.0612	70.5068
Δ% Selling For Loss	7158	0.107329	1.18954	-15.6326	16.4346
Turnover	7308	4.81494	2.253468	0.008869	17.16583
ΔTurnover	7271	0.0032471	0.106966	-12.71301	2.019346

Table 3.10: Descriptive Statistics of the Uncertainty Measures and the *bartik*.

	Obs.	Mean	Std. Dev.	Min	Max
Macro Uncertainty	264*51	0.67773	0.0961123	0.568981	1.130619
Policy Uncertainty	300*51	106.3401	34.38186	57.20262	245.1267
State Uncertainty	9180	18.23878	7.730284	0	233
VIX	300*51	19.9604	7.730284	10.82	62.64
bartik	15249	-0.000041	0.0001304	-0.002793	0.0009686

Sorted States in Subsection 3.3.3

Table 3.11: Sorted States, According to their Unconditional Housing Price Volatility over Time.

low	*medium*	*high*
Alabama	Alaska	Arizona
Arkansas	Colorado	California
Georgia	Delaware	Connecticut
Iowa	Idaho	District of Columbia
Indiana	Illinois	Florida
Kansas	Louisiana	Hawaii
Kentucky	Maine	Massachusetts
Missouri	Michigan	Maryland
Mississippi	Minnesota	New Hampshire
North Carolina	Montana	New Jersey
Nebraska	North Dakota	Nevada
New Mexico	Oklahoma	New York
Ohio	Pennsylvania	Oregon
South Carolina	Texas	Rhode Island
South Dakota	Utah	Virginia
Tennessee	Vermont	Washington
Wisconsin	West Virginia	Wyoming

Sorted States in Subsection 3.3.4

Table 3.12: Sorted States, According to the Impact of the *bartik* in Each State.

low	*medium*	*high*
Colorado	Arkansas	Alaska
Georgia	Kansas	Arizona
Iowa	Massachusetts	District of Columbia
Illinois	Maryland	Delaware
Kentucky	Minnesota	Hawaii
Louisiana	Missouri	Maine
Michigan	North Dakota	New Hampshire
Mississippi	Nebraska	New Mexico
North Dakota	New Jersey	Oregon
New York	South Carolina	South Dakota
Oklahoma	Virginia	West Virginia
Tennessee	Washington	Wyoming
Texas		

CHAPTER 4

Uncertainty and Trade

This chapter consists of two sections. Section 4.1 quantifies the impact of macroeconomic uncertainty shocks on disaggregated German import flows using a classification scheme[1] from the German Engineering Association (www.vdma.org), which categorizes manufacturing goods into intermediate and final goods. In order to enhance the understanding of this classification scheme, section 4.2[2] applies this scheme to European trade data and provides descriptive statistics as well as causality analyses of trade flows of the EU-27 countries.

4.1 Uncertainty and Trade: Evidence from Germany

Abstract: This paper quantifies the impact of macroeconomic uncertainty shocks on the disaggregated German import flows. Structural VAR (SVAR) estimations reveal that a one standard deviation increase in macroeconomic uncertainty induces a decline in total import, import of intermediate manufacturing goods and import of final manufacturing goods by 1.04%, 1.43% and 1.44%, respectively. The findings suggest that uncertainty shocks in one

[1]I am grateful to Prof. Dr. Richard Frensch and the Institute for East and Eastern European Studies in Regensburg (IOS) for sharing their data with me.

[2]This section is based on joint work with Stephan Huber and was published in a journal (Huber and Thanh, 2017).

country affect production in another through the trade channel.

4.1.1 Introduction

Uncertainty shocks are considered to be an important driver of the real economy. Christiano et al. (2014) argue that time-varying uncertainty is the most important driver of the business cycle and other studies suggest a decline in investment in response to uncertainty shocks (e.g., Bernanke, 1983; Bloom, 2009; Meinen and Roehe, 2017). In the same vein, Karnizova and Li (2014) find that the economic policy uncertainty measure proposed by Baker et al. (2016) is a robust predictor of U.S. recessions. Moreover, Leduc and Liu (2016) show that an increase in uncertainty induces a rise in the unemployment rate and Dorofeenko et al. (2014) conclude that uncertainty shocks account for over 90% of the U.S. house price volatility.

While most studies focus on the impact of uncertainty within a country, there are also works on the cross-border effects of uncertainty shocks. Colombo (2013) estimates Structural Vector Autogregression (SVAR) models and documents that a one standard deviation U.S. economic policy uncertainty shock decreases European industrial production by 0.12%. Similarly, the SVAR estimations of Mumtaz and Theodoridis (2015) show that a one standard deviation increase in the volatility of U.S. real activity shocks leads to a 1% decline in U.K. GDP.

Nevertheless, it remains unclear through which channel(s) a domestic uncertainty shock affects real activity in foreign economies. The current paper seeks to clarify this question and investigates whether the trade channel plays an important role in transmitting uncertainty shocks in one country on production in another. The theoretical model of Novy and Taylor (2014) predicts that manufacturing firms cut the import of intermediate goods in response to a rise in uncertainty, while Bloom (2014) suggests the rise of precautionary savings and thus lesser consumption which, in turn, translates into a decrease of the import of final consumption goods during periods of high uncertainty. Using German disaggregated trade data, I empirically test these two predictions. SVAR estimations indicate that a one standard deviation increase in uncertainty lowers the import of intermediate manufacturing goods, the import of final manufacturing goods and the total volume of import in the middle-run by 1.43%, 1.44% and 1.04%, respectively.

Subsection 4.1.2 presents the data and the estimation specification, while subsection 4.1.3 presents the estimation results. Finally, subsection 4.1.4

concludes.

4.1.2 Data and Econometric Specification

I use disaggregated Combined Nomenclature 8 digit-level monthly Comext trade data from Eurostat from 1996M6 to 2015M3[3] and a classification scheme from the German Engineering Association (www.vdma.org) that categorizes traded manufacturing goods into parts, components and final goods. In this section, I interpret both parts and components as intermediate goods. On average, 11% of total import is classified as the import of manufacturing goods. Table 4.3 in the Appendix of section 4.2 shows examples of the most traded intermediate and final goods and section 4.2 provides a detailed discussion on this classification scheme and the disaggregated trade data.

Furthermore, I use a measure for the German macroeconomic uncertainty (*German Macro Uncertainty*) which is analogous the *Macro Uncertainty* proposed by Jurado et al. (2015), but proxies the average uncertainty of German macroeconomic series. *German Macro Uncertainty* is provided by Meinen and Roehe (2017) who use 143 macroeconomic time series for the computation. This measure captures the predictability of the overall macroeconomic environment; the less predictable the macroeconomic variables, the higher the macroeconomic uncertainty. I use the one-month-ahead measure, since the data are at a monthly frequency. Using a similar measure for macroeconomic uncertainty which is proposed by Rossi and Sekhposyan (2015) leads to the same conclusions[4].

I also include the DAX, the German industrial production in the manufacturing section ($production$) and the German employment ($employment$) in the SVAR estimation. These data were collected from Thomson Reuters Datastream. The import data, $production$ and $employment$ are seasonally adjusted, and all variables are Hodrick-Prescott (HP) detrended (λ =129,600), analogous to Bloom (2009) and Novy and Taylor (2014).

I use the following SVAR representation:

$$B_0 y_t = B(L) y_{t-p} + e_t, \tag{4.1}$$

[3]The Macro Uncertainty measure is not available for earlier periods.
[4]The estimation results are presented in the Appendix.

where $y_t = \begin{pmatrix} log(DAX) \\ \textit{German Macro Uncertainty} \\ log(production) \\ log(employment) \\ log(importvariable) \end{pmatrix}_t$, e_t is the vector of structural innovations, $B(L)$ an autoregressive lag-polynomia and B_0 the matrix containing the contemporaneous relationships between the reduced-form residuals and the structural innovations. I use a standard Cholesky decomposition imposing a lower triangular matrix to identify B_0. Following Bloom (2009) and Novy and Taylor (2014), I use the ordering[5] $log(DAX)$, *German Macro Uncertainty*, $log(production)$, $log(employment)$ and $log(importvariable)$. I follow the recommendation of the Schwarz Criterion and decided to choose two lags in the benchmark specification. However, the results are robust to alternative lag specifications.

4.1.3 Estimation Results

Figure 4.1 depicts the impulse response functions of the import variables to a one standard deviation shock to *German Macro Uncertainty*. A one standard deviation increase in *German Macro Uncertainty* significantly lowers the import of intermediate manufacturing goods and final manufacturing goods as well as the total volume of import in the middle-run, reaching a maximum level of impact of 1.43%, 1.44% and 1.04%, respectively. The reduction of the import of intermediate goods in response to an increase in uncertainty is in line with the prediction of the model of Novy and Taylor (2014). In the model, firms face fixed costs of ordering from abroad and thus store intermediate goods according to an inventory policy. Firms respond to uncertainty shocks by contracting their inventory policy and cutting their import of intermediate goods. On the other hand, the decline of the import of final goods indicates the rise of precautionary savings and therefore lower consumption as suggested by Bloom (2014). It is worth nothing that the reactions of the import of intermediate goods and the import of final goods to an uncertainty shock are qualitatively and quantitatively similar. This observation indicates that the cutting of foreign import of intermediate goods is similar to the reduction of consumption of goods from abroad. Moreover, while Bloom (2009) finds that following an uncertainty shock output, employment and productivity decline

[5] The main results are robust to alternative order specifications.

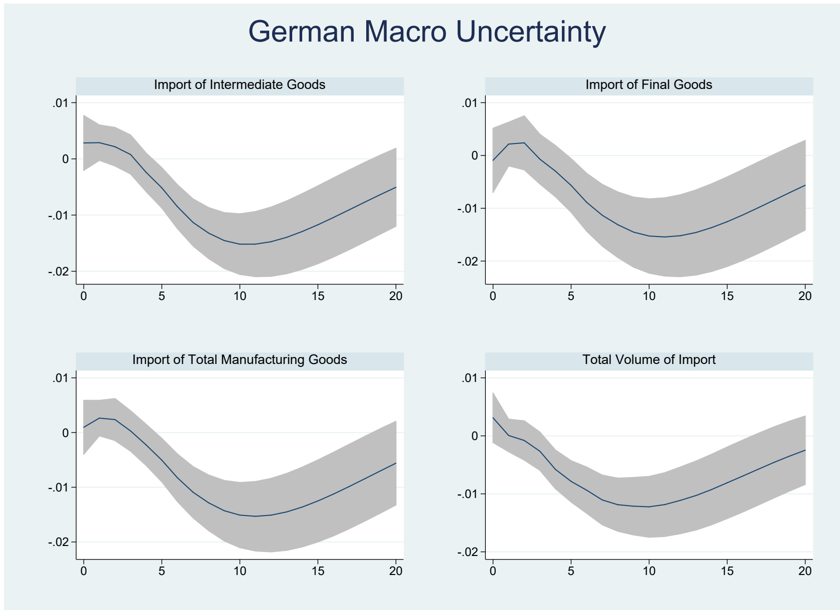

Figure 4.1: Impulse Response Function of Import Variables to a *German Macro Uncertainty* Shock

Note: The sample period is 1996M6-2015M7. The figure displays the response of import variables to a one standard deviation *German Macro Uncertainty* shock. The shaded areas denote the 95% confidence intervals from multivariate parametric bootstrap procedures with 2000 replications.

for some periods and overshoot in the recovery phase, the import variables do not show a comparable overshooting reaction.

Figure 4.2 illustrates the relative importance of a *German Macro Uncertainty* innovation in explaining the forecast error variance of the import variables. The forecast error variance decomposition confirms the finding that the impact of a *German Macro Uncertainty* shock is more important in the middle-run and not in the short-run. There is a very low level of contribution of an innovation in *German Macro Uncertainty* to the total forecast error variances of the import variables in the first 5 months, but the levels of contribution rise sharply in the middle-run and reach 35% (intermediate goods), 25% (final goods) and 33% (total volume of import) after 15 months.

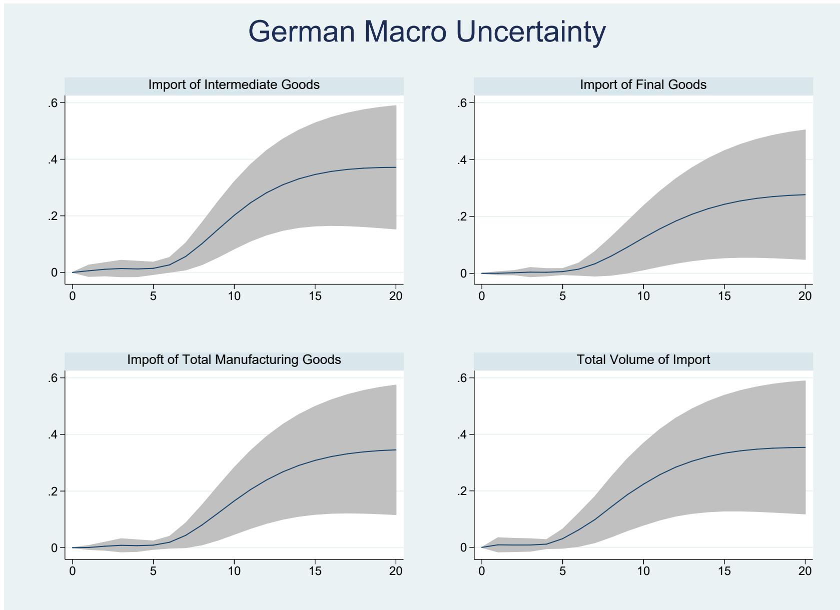

Figure 4.2: Forecast Error Variance Decomposition Due to an Innovation in *German Macro Uncertainty*

Note: The sample period is 1996M6-2015M3. The shaded areas denote the 95% confidence intervals from multivariate parametric bootstrap procedures with 2000 replications.

4.1.4 Conclusion

I use German data to investigate the impact of macroeconomic uncertainty on import flows. SVAR estimations reveal that a rise in *Macro Uncertainty* lowers the import of intermediate manufacturing goods, final manufacturing goods and the total volume of import. The magnitude of reaction to an uncertainty shock of the import of intermediate goods is comparable to the one of the import of final goods. The reduction of import following an uncertainty shock in a country equates with a lower export of its trade partners which cools down the production in those partner countries. This mechanism helps to understand why there are cross-border spillover effects of uncertainty shocks.

Appendix

Data Appendix

- Disaggregated trade data are collected from Eurostat (http://ec.europa.eu/eurostat/de/data/database).

- *German Macro Uncertainty* is provided by Meinen and Roehe (2017) (http://www.sciencedirect.com/science/article/pii/S0014292116302239).

- Macroeconomic uncertainty by Rossi and Sekhposyan (2015): the authors propose an alternative measure of macroeconomic uncertainty which quantifies the unpredictable components of GDP. They extract the unforecastable component from GDP and, subsequently, evaluate the cumulative density of forecast errors at the actual realized forecast error. Meinen and Roehe (2017) follow the approach of Rossi and Sekhposyan (2015) and calculate for a wide range of macroeconomic variables a corresponding uncertainty measure and compute the arithmetic mean across all uncertainty series. This arithmetic mean measure of uncertainty, which is based on a multitude of macroeconomic variables, is used for the computation of 4.3. This measure for Germany is provided by Meinen and Roehe (2017) (http://www.sciencedirect.com/science/article/pii/S0014292116302239).

Supplementary Graph

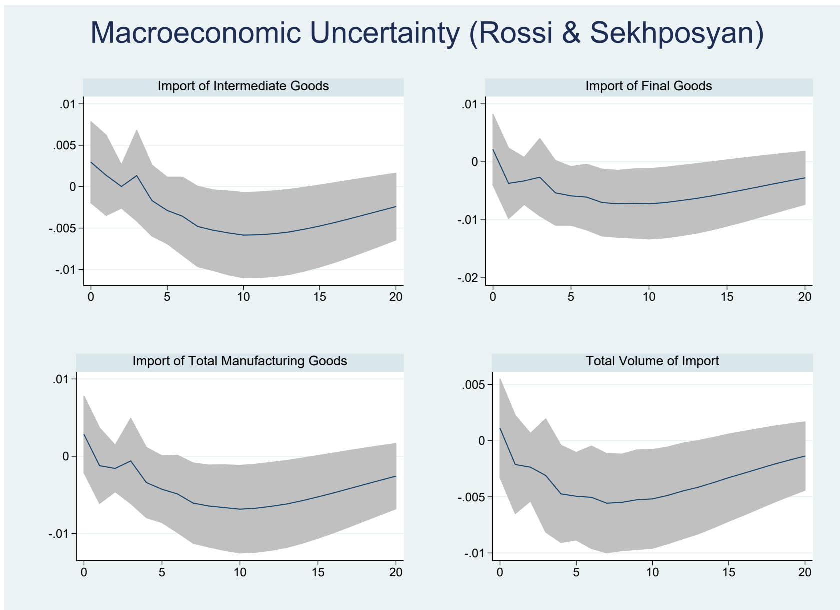

Figure 4.3: Response of Import Variables to a One Standard Deviation Macroeconomic Uncertainty Shock Which Is Proposed by Rossi and Sekhposyan (2015)

Note: The sample period is 1996M7-2015M3. The macroeconomic uncertainty measure by Rossi and Sekhposyan (2015) for Germany is computed and provided by Meinen and Roehe (2017).

4.2 Vertical Specialization in the EU and the Causality of Trade.

Abstract: We[6] use a novel classification scheme to identify three stages of production in the manufacturing sector: parts, components, and final goods. In particular, we offer evidence on the revealed comparative advantage of the EU-27 countries concerning the three vertically separated stages of production. Moreover, we investigate whether, and if so how, imports of parts, and components can work as a predictor for the exports of final goods. We find that countries specialize at different stages of production, and that components are Granger causal for the export of final goods in many countries with a lag of three months.

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[6]We are grateful to the Institute for East and Eastern European Studies in Regensburg (IOS) for sharing their data with us. In particular, we are grateful to Richard Frensch, Volkhart Vincentz as well as all IOS-seminar participants.

4.2.1 Introduction

The share of intermediates in intra-EU trade is increasing and reaches almost 50% nowadays.[7] Although some widely received articles, such as Hummels et al. (2001), Feenstra (1998), or Grossman and Rossi-Hansberg (2006), have addressed the issue of how countries specialize along the vertical production chain, surprisingly little is known about the comparative advantage and the causal interrelationship of international trade in parts, components, and final goods. The research gap can be explained with a lack of data that allows to distinguish traded goods at vertically separated stages of production that goes beyond the dichotomy of 'parts&components' and 'final goods'. We aim to fill this gap by using a novel categorization scheme compiled by experts of the German Engineering Association (`www.vdma.org`), which categorizes traded manufacturing goods at the highly disaggregated CN-8 digit-level into three vertically separated stages of production: (1) parts, (2) components, and (3) final goods. Overall, we identify 245 products as parts, 329 products as components, and 1058 products as final goods within the manufacturing sector.[8] This trisection allows us to overview the comparative advantage of countries at different stages of production and to investigate whether the imports of parts and components can help to predict exports of goods at the final stage of assembling.

In our analysis, we employ Granger causality tests revealing that imports of parts and components help to predict the export of final goods. This holds especially true for countries with a high revealed comparative advantage in the export of final goods. However, the import of components are often sufficient to improve the prediction about exports of final goods. The chosen lag length is quite often three month, which can be interpret as the time it takes to assemble and export a final good. The causal impact of less differentiated imports in parts, however, seems to play a minor role. The intuition of this result is that components have a smaller range of use in the production system and hence are often specifically build to work as a preliminary input

[7] We refer to Guerrieri and Caffarelli (2012) for an overview how the international fragmentation of production has developed.

[8] Parts contains commodities like electronic instruments, mechanical seals, sewing machine needles with single flat shank, and spinning rings. The intermediate class components contains commodities such as engines and motors, air conditioning machines, temperature regulators, or articulated shafts. Final goods classify manufacturing commodities such as gas turbines, digger, lifts, or mobile cranes. For some further examples of the categorisation we refer to Table 4.3 in the Appendix.

for a small range of final manufacturing goods.

The remainder of the paper is structured as follows. Subsection 4.2.2 introduces the data and offers some descriptive facts concerning the countries' revealed comparative advantage. Subsection 4.2.3 asks, whether imports of parts and components are Granger causal for exporting final goods. Subsection 4.2.4 concludes.

4.2.2 Data and Comparative Advantage

We use de-seasonalized (X-12-ARIMA adjusted) monthly COMEXT trade data from Eurostat from 1988M1 to 2015M8 for 27 EU countries. Table 4.1 contains the number of observations for each country, which vary from 188 to 332, as well as the share of exports and imports captured by parts (p), components (c), and final goods (f), which vary from about three percent (Ireland and Greece) to over twenty percent (Italy and Germany[9]).

Table 4.1 contains the Revealed Comparative Advantage index (RCA)[10] for parts, components, and other goods (o) for exports and imports, respectively. We calculate the RCA using the average export and import flows from 2004 to 2013. In this time span our sample is balanced and it is long enough to smooth out disturbing effects from temporarily economic shocks. The results reveal that some countries, like Austria, Germany, Denmark, Finland, Italy, and Sweden do have a general comparative advantage in exports of manufacturing goods, while other countries, like Czech Republic, Portugal, Romania, Slovakia, and Slovenia specialize only in earlier stages of production.

An interesting observation is Germany, since recent literature, such as Sinn (2006), emphasize that Germany is a 'bazaar economy' which imports early stages of production to assemble them and export final goods. Our results support this hypothesis: Germany has a RCA in importing parts (1.21) and components (1.18) and a relative high RCA in exporting final goods (1.52) compared to the RCA in exporting parts (1.23) and components (1.4). The RCA of Portugal, Romania, and Slovakia in the export of components is also remarkably high. This could be driven by some large firms of the automotive industry who offshore early and intermediate stages of production into these

[9]Germany is denoted as "DEU".

[10]It is defined by $RCA_{ij} = \frac{x_{ij}/\sum_j x_{ij}}{\sum_i x_{ij}/\sum_j \sum_i x_{ij}}$, where x_{ij} denotes the exports or imports in good class i of the declaring country j.

countries.

Table 4.1: Revealed Comparative Advantage in Parts, Components and Final Goods

	RCA_p^{ex}	RCA_c^{ex}	RCA_f^{ex}	RCA_o^{ex}	RCA_p^{im}	RCA_c^{im}	RCA_f^{im}	RCA_o^{im}	S_{Ex}	S_{Im}	Obs.
AUT	1.22	1.22	1.35	.95	1.41	1.54	1.48	.95	.21	.157	248
BEL	.64	.65	.46	1.07	.77	.83	.76	1.02	.078	.079	200
BGR	.58	.79	.52	1.07	.85	.72	1.35	.99	.086	.115	188
CYP	.16	.08	.46	1.11	.46	.41	.92	1.03	.048	.077	188
CZE	1.37	1	.98	.99	1.38	1.35	1.25	.97	.168	.14	188
DEU	1.23	1.4	1.52	.93	1.21	1.18	1.05	.99	.231	.108	332
DNK	1.39	1.17	1.28	.96	1.3	1.37	1.16	.98	.194	.124	332
ESP	.55	.54	.63	1.06	.77	.89	.91	1.01	.085	.095	332
EST	.73	.24	.75	1.05	.63	.72	1.3	1	.096	.107	188
FIN	1.22	1.03	1.48	.95	1.12	1.23	1.15	.98	.193	.121	248
FRA	.77	.88	.7	1.04	.96	.96	1.01	1	.106	.099	332
GBR	.92	.79	.79	1.03	.87	.83	.93	1.01	.128	.093	332
GRC	.22	.12	.33	1.11	.5	.48	.77	1.04	.035	.077	332
HUN	.95	.82	.76	1.03	1.32	1.53	1.8	.94	.12	.18	188
IRL	.41	.14	.24	1.11	.79	.47	.73	1.03	.034	.072	332
ITA	1.51	1.69	1.59	.91	.86	1.08	.86	1.01	.256	.09	332
LTU	.32	.43	.65	1.07	.63	.61	1.1	1.01	.079	.09	188
LUX	.86	.81	.31	1.07	.81	.57	.59	1.04	.078	.066	200
LVA	.33	.38	.65	1.07	.65	.7	1.31	1	.076	.109	188
MLT	.4	.18	.36	1.1	.65	.33	.78	1.03	.043	.07	188
NLD	.92	.45	.61	1.05	1.03	.67	.7	1.02	.088	.077	332
POL	.63	.66	.84	1.04	.94	1.2	1.45	.97	.115	.134	188
PRT	.33	1.01	.57	1.06	.7	.64	.95	1.02	.073	.091	332
ROM	.84	1.21	.52	1.05	1.18	1.05	1.46	.97	.104	.139	188
SVK	.82	1.07	.55	1.05	1.05	1.11	1.08	.99	.104	.113	188
SVN	1.2	.88	.93	1	.92	1.02	1.1	1	.152	.109	188
SWE	1.33	1.31	1.01	.98	1.28	1.32	1.22	.97	.178	.135	248

S_{Ex} and S_{Im} denote the share of total export and the share of total import which is categorized as manufacturing goods, respectively.

4.2.3 Causality

In this section, we ask whether imports of preliminary and intermediate goods are Granger causal for the exports of final goods. To investigate whether the import of parts (im_p) and components (im_c) is Granger causal for the export of final goods (ex_f), we estimate for each country:

$$\begin{aligned}\Delta log(ex_f)_t =& \beta_0 + \sum_{j=1}^{p} \Delta log(im_p)_{t-j}\beta_j \\ &+ \sum_{j=1}^{p} \Delta log(im_c)_{t-j}\gamma_j \\ &+ \sum_{j=1}^{p} \Delta log(ex_f)_{t-j}\delta_j + u_t. \end{aligned} \quad (4.2)$$

whereby we use the Akaike (AIC) and Schwarz information criterion (SIC) to choose an appropriate lag length p. In order to test the relevance of im_p and im_c, respectively, we employ two tests: The first one is a Granger causality test with:

$$H_0 : \beta_1 = \cdots = \beta_p = \gamma_1 = \cdots = \gamma_p = 0. \quad (4.3)$$

The second test checks whether an increase of imports in parts and components lead to an increase of exports of final goods:

$$H_0 : \beta_1 + \cdots + \beta_p + \gamma_1 + \cdots + \gamma_p \leq 0. \quad (4.4)$$

If both tests can be rejected, im_p and im_c are positive Granger causal for ex_f.

Instead of presenting 27 regressions and its corresponding test statistics, we summarize our results in Table 4.2. The fourth column denotes the results for estimating and testing equation (4.2). To test whether the imports of parts or components solely determine the exports of final goods, we show in the second and third column the results for specifications which omit from our baseline specification components (im_2) and parts (im_1), respectively. We abbreviate the results as follows: a star ($*$) indicates a rejection of the first test, a plus (+) denotes a rejection of the second test, both at a 5% significance level. The superscript number denotes the chosen lag length following the Schwarz Information Criterion (SIC) and the Akaike information criterion (AIC). The table contains results for both selection criteria, whereby the results for the AIC are shown in brackets.

Following the SIC, imports of parts are positive Granger causal for Italy

Table 4.2: Summary of the Causality Analysis using SIC (AIC)

	$im_p \rightarrow ex_f$	$im_c \rightarrow ex_f$	$im_{p,c} \rightarrow ex_f$
AUT	$*^{2}(*+^{6})$	${}^{2}(*^{9})$	$*^{2}(*+^{9})$
BEL	$*^{3}(*+^{4})$	${}^{3}(+^{6})$	$*^{3}(*+^{4})$
BGR	${}^{1}({}^{2})$	${}^{1}({}^{2})$	${}^{1}({}^{2})$
CYP	${}^{3}({}^{6})$	${}^{2}({}^{6})$	${}^{2}({}^{6})$
CZE	${}^{3}(+^{5})$	${}^{3}(*+^{4})$	${}^{3}(*+^{4})$
DEU	${}^{3}(+^{4})$	$*+^{3}(*+^{5})$	$*+^{3}(*+^{4})$
DNK	${}^{2}({}^{4})$	${}^{2}(*^{4})$	$*^{2}(*^{4})$
ESP	$+^{2}(+^{3})$	$*+^{3}(*+^{9})$	${}^{2}(*+^{3})$
EST	${}^{2}(+^{2})$	$*+^{2}(*+^{9})$	${}^{1}(*+^{9})$
FIN	${}^{2}(*+^{6})$	${}^{2}(*+^{10})$	${}^{1}(*+^{7})$
FRA	$*^{3}(*^{10})$	$*+^{3}(*+^{10})$	$*+^{3}(*+^{8})$
GBR	$*^{2}(*^{12})$	$*+^{3}(*+^{9})$	$*+^{3}(*+^{9})$
GRC	$*^{7}(*^{12})$	$+^{7}(+^{12})$	$*+^{7}(*^{12})$
HUN	$*^{3}(*^{5})$	${}^{1}({}^{12})$	${}^{1}(*+^{5})$
IRL	${}^{2}({}^{2})$	${}^{2}({}^{8})$	${}^{2}({}^{2})$
ITA	$*+^{3}(*+^{8})$	$*+^{3}(*+^{8})$	$*+^{3}(*+^{8})$
LTU	${}^{1}(+^{5})$	${}^{1}({}^{4})$	${}^{1}({}^{1})$
LUX	$*^{3}(*+^{7})$	${}^{3}({}^{5})$	$*^{3}({}^{7})$
LVA	${}^{2}(*^{5})$	${}^{2}(*^{7})$	${}^{2}(*+^{7})$
MLT	$*^{6}(*^{11})$	$+^{6}(+^{10})$	$*+^{6}(+^{10})$
NLD	${}^{2}({}^{2})$	${}^{2}(*^{3})$	$*^{2}(*^{3})$
POL	$*^{2}(*^{4})$	$*^{3}(*^{4})$	${}^{1}(*^{4})$
PRT	${}^{2}({}^{3})$	$*^{2}(*^{3})$	$*^{2}({}^{3})$
ROM	${}^{2}(+^{2})$	${}^{2}({}^{2})$	${}^{2}({}^{2})$
SVK	${}^{3}(+^{4})$	${}^{2}(+^{6})$	$+^{3}(+^{4})$
SVN	$+^{1}(+^{11})$	${}^{1}(*^{12})$	${}^{1}(*^{12})$
SWE	${}^{2}(*+^{6})$	$*+^{3}(*+^{6})$	$*^{3}(*+^{6})$

* indicates Granger causality at 5% level, + indicates that overall effect is positive at 5% level, the superscript denotes the chosen lag length, the test results using the AIC criterion are displayed in brackets.

and imports of components are positive Granger causal for Germany, Spain, Estonia, France, Great Britain, Italy, and Sweden. With the exception of France and Great Britain, the results reveal that it is more likely to yield significant results for countries that have a comparative advantage in the export of final goods. For Estonia, the superior lag length is two, for all other countries it is three. This can be interpret as the time it takes for components to be assembled to final goods and in turn be exported. As the last column shows, the common inclusion of imports of parts and components yields significant and positive Granger causalities for Germany, France, Great Britain, Greece, Italy, and Malta. However, these Granger causalities are mostly driven by the imports of components, as the previous results can tell.

To explain the fact that we fail to find (positive) Granger causalities for all countries, one has to consider the nature and the limitations of our data: First, for some countries, the time series is rather short. This makes it difficult to find robust results, especially because we apply robust Newey-West[11] standard errors in our autoregressive model. More sophisticated models would require further information, such as which manufacturing parts are used to produce certain components and final goods. Second, imports of parts and components are not the only input-source to produce final goods. However, our data does not allow to capture non-manufacturing inputs from abroad or inputs that are not imported. Thus, it is unlikely to find causality for countries that export only a small share of their exports within the manufacturing goods that we capture with part, components, and final goods. This share is shown for the imports and the exports in Table 4.1. Third, we cannot control for the imports of parts and components that are used for self consumption and not to produce final goods for the export sector.

4.2.4 Concluding Remarks

This letter provides novel evidence on the export and import specialization concerning three different stages of production for EU-27 countries. Moreover, this paper shows that a more detailed classification of traded goods yield significant improvements of the prediction of exports of final goods, because it is predominantly the import of components that drives the exports of final goods. Parts, however, seem to play a minor role. Thus, countries with a revealed comparative advantage in the export of final goods tend to import

[11]See Newey and West (1987).

parts and components in order to assemble and export final goods. Of course, the results are borne by a simple empirical model and the time series are rather short for some countries. Nevertheless, we think our exercise helps to understand the global production sharing process further. Overall, we hope that this letter encourages future empiricism to apply more elaborated and detailed classification schemes.

Appendix

Data Appendix

Table 4.3: Example of Goods Categorized as Parts, Components or Final Goods

nc	Description
Parts:	
84159000	parts of air conditioning machines, comprising a motor-driven fan and elements f
84799080	parts of machines and mechanical appliances having individual functions, n.e.s.
84219900	parts of machinery and apparatus for filtering or purifying liquids or gases, n.
84819000	parts of valves and similar articles for pipes, boiler shells, tanks, vats or th
84139100	parts of pumps for liquids, n.e.s.
84149000	parts of : air or vacuum pumps, air or other gas compressors, fans and ventilati
84314980	parts of machinery of heading 8426, 8429 and 8430, n.e.s.
84119900	parts of gas turbines, n.e.s.
Components:	
82090020	inserts, indexable, for tools, unmounted, of sintered metal carbide or cermets
84818011	mixing valves for sinks, washbasins, bidets, water cisterns, baths and similar f
84148011	turbocompressors, single-stage (excl. compressors for refrigerating equipment an
84821090	ball bearings with greatest external diameter, 30 mm
84195000	heat-exchange units (excl. instantaneous heaters, storage water heaters, boilers
84812010	valves for the control of oleohydraulic power transmission
84807100	injection or compression-type moulds for rubber or plastics
84835080	flywheels and pulleys, incl. pulley blocks (excl. of cast iron or cast steel)
Final Goods:	
94036090	wooden furniture (excl. for offices or shops, kitchens, dining rooms, living roo
84433210	printers capable of connecting to an automatic data processing machine or to a n
84295210	self-propelled track-laying excavators, with a 360 °revolving superstructure
84099900	parts suitable for use solely or principally with compression-ignition internal
84862090	machines and apparatus for the manufacture of semiconductor devices or of electr
87084050	gear boxes for tractors, motor vehicles for the transport of ten or more persons
87019039	agricultural tractors and forestry tractors, wheeled, new, of an engine power
84798997	other

This table shows the eight most traded goods in the year 2012 within the respective goods category.

CHAPTER 5

Conclusion

The goal of this dissertation is to expand the understanding of the impact of economic uncertainty on economic activities by analyzing empirical data. There are robust and significant negative effects of uncertainty on financial, housing and trade markets, which indicate the occurrence of real options effects in those markets during periods of high uncertainty.

In chapter 2, time series estimations reveal that economic uncertainty shocks substantially impede the number of U.S. initial public offerings. Both the reduction of newly filed IPOs and the increase of withdrawn IPOs contribute to the overall decrease of the number of IPOs. Moreover, high economic uncertainty also depresses the IPO market condition variables, such as output, stock market growth and investor sentiment. Since high uncertainty shocks often persist for multiple quarters, they can hamper IPO issues for a considerable amount of periods and, thus, create cold IPO market phases. As high uncertainty dissolves, IPO-interested firms may want to go public in the same periods which could, in turn, generate hot IPO market phases. The described connection between uncertainty and the IPO timing provides an alternative and complementary explanation for the existence of IPO issue cycles.

Chapter 3 illuminates the impact of economic uncertainty on the housing market using a U.S. state level panel data set. We find a significant negative impact of uncertainty on the housing prices. Moreover, during periods of high uncertainty, housing market variables, such as housing price, median sell price, turnover rate and percentage of houses sold for loss are less responsive to labor demand shocks than in periods of low uncertainty. This finding suggests that the effect of uncertainty shocks dominates that of labor demand shocks and indicates that housing market variables react differently in periods of high uncertainty, which should be taken into account by policy makers.

Finally, chapter 4 quantifies the impact of macroeconomic uncertainty on German disaggregated import flows with SVAR estimations. The results indicate that an increase in uncertainty reduces the import of intermediate and final manufacturing goods as well as the total volume of import. The reduction of imports following an uncertainty shock offers a possible explanation for the question of why an uncertainty shock in one country affects economic activity in another.

For future research, further analyses on the lower responsiveness of economic agents to changes in the economic environment during periods of high economic uncertainty might be fruitful. In light of the findings of this dissertation, I conjecture that, for example, the impact of fiscal stimulus packages or monetary policy is less effective during times of high uncertainty. Furthermore, it might be rewarding to study the nonlinear effects of uncertainty shocks, since the effects of an increase in uncertainty may not be symmetrical with the effects of a decline in uncertainty. Other fertile ground for continuing research might be the identification of potential methods which could help to reduce the level of uncertainty. For instance, creditable policy commitment may remove the layer of uncertainty and encourage economic activity.

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