Related Literature

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Angeletos and La'O (2010) - NBER Macroeconomics Annual

They introduce heterogeneous information in a Real Business Cycle model. This assumption can have profound implications for the business cycle. They analyze a standard RBC model with no capital augmented with dispersed information frictions. In particular, economic decisions have to be made under heterogeneous information about the aggregate shocks hitting the economy. They summarize their results as follows. (i) Dispersed information induces inertia in the response of macroeconomic outcomes. (ii) Dispersion of information induces technology shocks to explain only a small fraction of the high-frequency variation in the business cycle. (iii) The drivers of the residual variation in the short-run fluctuations is simply the noise in available information, i.e. correlated errors in the agents' expectations of the fundamental shocks. (iv) These noise-driven fluctuations help formalize a certain type of demand shocks. (v) If a social planner takes information dispersion as given then equilibrium is already efficient implying no room for any intervention.

Importantly, what drivers their results is not per se the level of uncertainty about the underlying fundamental but rather the lack of common knowledge about it. Indeed, their effects are consistent with an arbitrary small level of uncertainty about the underlying fundamentals. However, at the same time, the lack of common knowledge alone does not explain the magnitude of our effects. What they need is also a degree of strategic complementary, which means that dispersed information has an effect if agents care on other agents' choices. Their findings hinge on the combination of heterogeneous information with strong strategic complementarity - but they do not hinge on the level of uncertainty about underlying fundamentals. In addition, notice that standard noise-shock literature obtains fluctuations that vanish when uncertainty on fundamentals is small enough.

Fluctuations are not generated by uncertainty regarding future exogenous fundamentals but by uncertainty regarding future choices of other agents that have different information. Specifically, when information is asymmetric agents face additional uncertainty about the level of economic activity beyond the one they face about fundamentals. It is specifically this feature that differentiated dispersed information different from uncertainty in fundamentals. Conversely, strategic complementary is irrelevant for business cycle fluctuations when information is commonly shared. Interestingly, the larger the level of strategic complementarity the less agents focus on fundamental shocks and the more they focus on public signals attempting to coordinate with each other. Thus, it follows that stronger strategic complementarity induces equilibrium to be more anchored to the past aggregate fundamentals, more sensitive to public information and less sensitive to private information.

Another important point that they stress is that the variance of the idiosyncratic signal received by agents is different from the degree of information dispersion. For example, if the variance of the idiosyncratic noise rises, agents might decide to rely less on their private signal focusing more on the public signal converging expectations and thus decreasing information dispersion.

Andrade, Crump, Eusepi, and Moench (2016) - JME

They study a collection of individual forecasts of real output growth, CPI Inflation and the FFR from the Blue Chip Financial Forecasts (BCFF) survey. They use this dataset to establish three novel stylized facts about forecasters' disagreement. (i) Forecasters disagree both about the sort term but also the medium- and long-run prospects of the economy. (ii) The disagreement among forecasters is time varying, even for long-term forecasts. (iii) The shape of the term structure of disagreement differs markedly across variables. In particular, the term structure of disagreement for GDP is upward sloping, for inflation fairly flat and for the policy rate downward sloping.

Thus, they rationalize those three key empirical facts with a generalized model of informational frictions which extends the Mankiw and Reis (2002) sticky information framework in two crucial dimensions. (i) It allows for a multivariate setup where agents update information about individual variables at different points in time. (ii) Macroeconomic variables are driven by unobserved short-term and long-term components, introducing an additional filtering problem for the agents. Notice that their model assumes that for each variable and in each period a random fraction of agents does not observe that variable realization. As a result, they do not assume that some agents are systematically more informed than others as in other models previously developed. This is an appealing property in light of the widely documented result that it is difficult to beat consensus forecasts of both survey participants and econometric models. The sticky information model captures the costs of processing the information available to produce a forecast update in the spirit of a rational inattention model. Interestingly, in their model disagreement is an increasing function of both noise and uncertainty.

The successfully calibrate the model to match previous empirical facts. They only struggle to reproduce the unconditional variance of disagreement over time. They also show that model's feature is able to rationalize disagreement on long-term policy rate accordingly with a standard policy rule.

Basu and Bundick (2017) - Econometrica

They argue that macroeconomic comovement is a key empirical feature of the economy's response to an uncertainty shock. Using a structural vector regression (VAR), they identify an uncertainty shock in the data as an exogenous increase in the implied volatility of future stock returns. They use a Cholesky decomposition with the VXO ordered first. This ordering assumes that uncertainty shocks can have an immediate impact on output and its components, but non-uncertainty shocks do not affect the implied stock market volatility impact. Empirically, an uncertainty shock causes statistically significant declines in output, consumption, investment, and hours, with a peak response occurring after about one year.

Under reasonable assumptions, an increase in uncertainty about the future induces precautionary saving and lowers consumption. Similarly, since both consumption and leisure are normal goods, an increase in uncertainty also induces precautionary labor supply. As current technology and the capital stock remain unchanged, the competitive demand for labor remains unchanged as well. Thus, higher uncertainty reduces consumption but raises output, investment, and hours worked. Yet intuition suggests that the reduction in household expenditure resulting from increased uncertainty could lead to a general decline in output and its components. This intuition is typically correct in models where output is demand-determined (at least over some horizon). In these models, the reduction of consumption demand reduces output and labor input which in turn reduces the demand for capital and hence investment. Aggregate demand-determined output is made consistent with household and firm optimization through endogenous movements in markups which in their model is driven by the standard assumption of nominal price rigidity.

To analyze the quantitative impact of uncertainty shocks, they calibrate and solve a representative-agent, dynamic, stochastic general-equilibrium (DSGE) model with capital accumulation and price rigidity. They examine the effects of second-moment shocks to household discount factors, which they interpret as demand uncertainty. When prices adjust slowly, uncertainty shocks can produce contractions in output and all its components. They calibrate the model using a mixed strategy between IRF-matching and unconditional moment matching. Using simulated data from their model, they show that their empirical identification strategy can recover the true macroeconomic effects of higher uncertainty.

Jurado, Ludvigson, and Ng (2015) - AER

At a general level, uncertainty is typically defined as the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents. In genera equilibrium settings, reasonable mechanisms imply a role for time-varying uncertainty. A challenge in empirically examining the behavior of uncertainty, and its relation to macroeconomic activity, is that no objective measure of uncertainty exists. Unfortunately, the conditions under which common proxies already used in the literature are likely to be tightly linked to the typical theoretical notion of uncertainty may be quite special. Their goal is to provide superior econometric estimates of uncertainty that are free as possible from theoretical impositions and specific-variable fluctuations. They emphasize that what matter for economic decision making is not whether particular economic indicators have become more or less variable or disperse per se, but rather whether the economy has become more or less predictable; that is, less or more uncertain. This implies that the proper measurement of uncertainty requires removing the forecastable component before computing conditional volatility.

Keeping into account previous feature (and also that uncertainty should not depend on a single variable but across the economy), they estimate measure of macroeconomic uncertainty using a monthly macro dataset and uses the information in hundreds of macroeconomic and financial indicators. They find significant independent variation in their estimates of uncertainty as compared to commonly used proxies for uncertainty. This is important because it suggests that much of the variation in common uncertainty proxies is not driven by uncertainty. An important finding is that their estimates imply far fewer large uncertainty episodes than what is inferred from all of the commonly used proxies we study. Moreover, their estimate of macroeconomic uncertainty is far more persistent that stock market volatility: 53 months vs 4 months.

Using an 11-variable monthly macro VAR and recursive identification procedure with uncertainty placed last, they find that common macro uncertainty shocks account for up to 29 percent of the forecast error variance in industrial production. This means that their estimates imply rare uncertainty episodes which are large, persistent and strongly related to economic activity. Although they find that increases in uncertainty are associated with large declines in real activities, they admit that their results are silent on whether uncertainty is the cause or effect of such declines.

Bloom (2014) - JEP

Frank Knight in 1921 defined uncertainty as peoples' inability to forecast the likelihood of events happening. In this article, Bloom refers to uncertainty as a broad mixture of risk and uncertainty. He addresses 4 questions about uncertainty. 1. What are some facts and patterns about economic uncertainty? 2. Why does uncertainty vary during business cycles? 3. Do fluctuation in uncertainty affect behavior? 4. Has higher uncertainty worsened the Great Recession and slowed the recovery?

1. First fact regarding uncertainty is that macro uncertainty rises in recessions. For example, VIX index of 30-days implied volatility on Standard & Poor's 500 stock market index is clearly countercyclical, rising by 58 percent on average in recessions. A second fact is that micro uncertainty rises in recessions. At every level (industries, firms, plants, ...), uncertainty appears to rise during recessions. For example, Campbell et al. (2001) report that cross-firm stock-return variation is almost 50 percent higher in recession that booms. Third, since unemployment rises during recession so the volatility of household incomes will rise as well. However, also wages for even those who are employed also become more volatile during recessions. Finally, uncertainty is higher for developing countries.

2. What factors might be causing these variations in uncertainty? In general, dramatic shocks seem to shake people's confidence in their forecasts of economic growth, raising macro and micro uncertainty. Conversely, positive shocks do not have a large impact on uncertainty. An explanation might be that positive news tend to develops gradually (internet, ...). The theory literature highlights four mechanisms through which recessions might increase uncertainty. (i) During expansions firms are trading actively which help to generate and spread information. (Viceversa during recessions.) (ii) Individuals are more confident in predicting the future when business as usual prevails in growing

economy. Recessions are rare events and since individuals are unfamiliar with them, they find harder to provide good forecasts. (iii) Unconventional or unusual policies to fight recessions may rise uncertainty. (iv) When business cycle is slack is more convenient to divert unused resources in R&D. This dynamic leads to larger macro uncertainty since outcomes are ex ante unclear.

Uncertainty tends to be higher in developing countries because they are (i) less-diversified economies, (ii) appear to have more domestic political shocks (revolutions, ...) or natural disasters (epidemics, ...), and (iii) have less effective stabilization policies.

3. To what extend uncertainty matters? Theoretically speaking many channels can affect real activities through uncertainty. **Real Options.** The idea is that firms can look at their investment choices as a series of options. As a result, uncertainty makes firms cautious about actions like investment and hiring, which adjustment costs can make expensive to reverse. In addition, real-options channel makes economic actors less sensitive to changes in business conditions. this can make countercyclical economic policy less effective. Notice that this channel whereby uncertainty reduces firms' sensitivity also provides an explanation for procyclical productivity. When uncertainty is high, productive firms are less aggressive in expanding and unproductive firms are less aggressive in contracting. The high uncertainty makes both of them more cautious implying a slowdown in productivity. **Risk Aversion and Risk Premia.** Investors want to be compensated for higher risk, and because greater uncertainty leads to increase risk premia this should raise the cost of finance. Moreover, a rise in uncertainty leads consumers to increase their precautionary saving, which reduces consumption expenditure. Weak consumption demand is contractionary in partially demand-driven models or in open economy (Fernandez-Villaverde et al. 2011). **Growth Options.** When business cycle is slack is more convenient to divert unused resources in R&D. Although this dynamic leads to larger macro uncertainty since outcomes are ex ante unclear, it also leads to larger TFP growth in the long run. **Oi-Hartman-Abel Effects.** This effect highlights the possibility that if firms can expand to exploit good outcomes and contract to insure against bad outcomes, they may be risk loving. However, for this mechanism to work, firms need to be able to easily expand or contract in response to good or bad news.

   Empirically speaking, the evidence on the impact of uncertainty is limited because of the difficulties in stripping out cause and effect. To identify the causal impact of uncertainty on firms and consumers, the literature has taken three approaches: (i) Estimating the movements in output, hiring, and investment that follow jumps in uncertainty. (ii) Analyzing structural models calibrated from macro and micro moments to quantify the potential effect of uncertainty shocks. (iii) Exploiting natural experiments where uncertainty arise from exogenous events.

4. Which is the role of uncertainty during the Great Recession and its aftermath? Policymakers clearly think uncertainty has played a central role in driving the Great Recession and slow recovery. However, the econometric evidence is really no more than suggestive.

Berger, Dew-Becker, and Giglio (2019) - REStud

This paper aims to estimate the magnitude of the effects of aggregate uncertainty shocks on economic activity. The major identification problem they face is that uncertainty about the future tends to be related to current economic conditions. Their key distinction from past work is to construct shocks to uncertainty that are orthogonal to current (relized) volatility. **Realized volatility** measures how large are the shocks that have just occurred, whereas **uncertainty** (implied volatility) is about how large agents expect future shocks to be. Models of the effects of uncertainty are driven by variation in agents' subjective distributions of future shocks, as opposed to the variance of the distribution from which today's shocks were drawn. Past work found that shocks to stock market volatility, measured as a mixture of realized and expected future volatility, have negative effects on the economy. They show that the distinction between realized volatility and news about the future (implied volatility) is critical for understanding the effects of uncertainty shocks. When uncertainty shocks are properly defined as forward looking, they actually have no effects on the economy. Rather it is current realized volatility that is associated with downturns and drives the previous results. While there are many models explaining how uncertainty shocks might drive the economy, there are no current models available matching our findings that uncertainty shocks are not contractionary while realized volatility shocks are. The last section of the paper presents a simple purely rational model that quantitatively matches our evidence. Its key mechanism is that shocks to technology are negatively skewed. Negative skewness means that large shocks - which cause high realized volatility - also tend to be negative shocks, immediately generating the observed negative correlation between realized volatility and output. Their finding that realized volatility per se is associated with contractions does not therefore imply that realized volatility per se is contractionary - it can be simply capturing the occurrence of a large negative shock.[1]

Empirically, they ran a Structural VAR with aggregate monthly US data which embodies realized volatility, implied volatility, industrial production, and employment. All variables are in log. Realized volatility is defined as the monthly average of the daily stock return of the S&P 500 index. Implied volatility is extremely close to the VIX and other relater model-free implied volatility. They identify a realized volatility shock as the residual of realized volatility from the reduced-form VAR (as a Cholesky identification with realized volatility ordered first). They identify an uncertainty shock (implied-volatility shock) as a shock that have zero-impact effect on realized volatility and whose variance of expected future realized volatility is equal to the one explained by a realized volatility shock on the same variable. They obtain that a realized volatility shock is associated with contractions on both employment and industrial production capturing the intuition that higher realized volatility is related to large negative (fundamental) shocks. Surprisingly, an uncertainty shock has no effect on employment and industrial production when using sufficiently tight confidence bands.

Leduc and Liu (2016) - JME

In the empirical section they examines the macroeconomic effects of uncertainty shocks in the data. They consider two alternative measures of uncertainty: (i) VIX and (ii) a new measure of consumers' perceived uncertainty constructed from the University of Michigan Surveys of Consumers. This last measure asks consumers if they are going to buy or not a durable good in the next period and the reason why they are not going to buy it. Among the options there is also uncertain future. They broadly use this specific type of answer to measure uncertainty. Although the time series behaviors of these two measures of uncertainty are quite different, the macroeconomic effects of uncertainty shocks based on the two different measures are remarkably similar.

The baseline BVAR contains four time-series variables: 1. a measure of uncertainty, 2. the unemployment rate, 3. the inflation rate (CPI), and 4. the 3-month Treasury bills rate. Thus, they use a Choleski decomposition which implies that the

[1]This is what they say: A jump in stock prices, such as a crash or the response to a particularly bad macro data announcement, mechanically generates high realized volatility. On the other hand, news about future uncertainty, such as an approaching presidential election, increase expected volatility. *I personally do not believe that high nonfundamental news does not affect stock prices. This is not what I expect. I need to dig in. Indeed, realized volatility and implied volatility have correlation extremely close to 1. If an uncertainty shock cannot have impact on realized volatility then what is left?*

uncertainty variable does not respond to macroeconomic shocks in the impact period, but macro variables are allowed to respond to an uncertainty shock. Similarly to Basu and Bundick (2017) an uncertainty shock is contractionary with an effect that last at most 4 years. They claim that since the impact effect on macro variables is very small an uncertainty shock can be also ordered last without deeply affecting the result. To assess the extend to which consumer uncertainty might reflect their perceptions of bad economic times, they also control in the VAR for another indicator of economic conditions: consumer sentiment index.[2]

In the theoretical section, they examine transmission channels of uncertainty shocks in a DSGE model with sticky prices and labor market search frictions. They show that an uncertainty shock in the DSGE model acts like an aggregate demand shock that raises unemployment, lowers inflation, and through the Taylor rule, lowers the nominal interest rate, as in the data. In the DSGE model, search frictions in the labor market and sticky prices in the good market are both important for amplifying the effects of uncertainty shocks. In particular, search frictions are related to the option-value channel. Uncertainty creates a precautionary motive that reduces the real interest rate. All else equal, a reduction in the real interest rate raises the present value of a job match and thus raises employment and output. However, a model with search frictions implies that a job match represents an irreversible long-term employment relation. Uncertainty then gives rise to a real option-value effect that is contractionary. Facing higher uncertainty, the option value of waiting increases and the expected value of a job match decreases, inducing firms to post fewer vacancies, making it harder for unemployed workers to find jobs, and ultimately raising the equilibrium unemployment rate. The intuition for sticky prices and policy rate is similar to the one provided by Basu and Bundick (2017).[3]

When the model is augmented with both frictions, simulated data generate an unemployment response to uncertainty with a size close to that estimated from the BVAR model. Thus, this interaction is important for amplifying the macroeconomic effects of uncertainty shocks.

[2] My personal comment is that they order this indicator as second implying that they do not control for a jump in uncertainty due to a contemporaneous fundamental shock. I am pretty sure, and I may control for it that if you reverse the ordering between the first two variables uncertainty does not explain anything as Berger et al. (2019).

[3] They claim that following Born and Pfeifer (2014), in a standard model without search frictions, habit formation dampens the effect of uncertainty on economic activity, since the consumption declines is more muted in this case. In their model instead, habit formation amplifies responses.

Cascaldi-Garcia and Galvao (2019) - JMCB

They show that news and uncertainty shocks are positively related using standard procedures. Their result is robust when they focus on financial uncertainty but not significant if they focus on macroeconomic uncertainty. When an uncertainty shock hits the economy, utilization-adjusted TFP increases over the medium run implying an attenuation bias of the negative impact of increasing uncertainty on economic activity.[4]

They define good uncertainty shocks the ones related to news (future increase in TFP) and bad uncertainty shocks as the ones not related to news. Obviously, bad uncertainty shocks play a larger role on over short horizon since they do not suffer of the attenuation bias of positive TFP.

News shocks are positive related to financial uncertainty in the medium run. This result has been already confirmed by Bloom (2009), Matsumoto et al. (2011), and Gortz et al. (2016). However, the persistent positive effect of financial uncertainty shocks on productivity might be seen as counterintuitive since TFP should decrease in the short run due to the effect of wait-and-see where productive firms cease to expand and non productive firms cease to contract. They shed light on this puzzle by examining the response of non-adjusted TFP to uncertainty shocks. Non-adjusted TFP is now consistent with what expected implying that responses of productivity to uncertainty shocks reflect a combination of two effects: (i) a short-lived negative effect driven by a reduction of factor utilization and (ii) a positive medium-horizon effect generated by technology improvements.

Financial and uncertainty shocks only differ in the long-run, as uncertainty shock effects die out, whereas news shocks persist. Thus, they identify both news and uncertainty shocks in the same model such that we are able to measure their relevance in explaining business cycles variation. They use a VAR with 12 variables with aggregate quarterly US data. They define **good uncertainty shocks** the ones related to news (future increase in TFP) and **bad uncertainty shocks** as the ones not related to news, i.e. the once where they sequentially control for news. Obviously, bad uncertainty shocks play a larger role on over short horizon since they do not suffer of the attenuation bias of positive TFP. Importantly, the relative importance of news and financial uncertainty shocks depends on whether we are able to assume that technology news shocks are orthogonal to financial uncertainty.

[4] I personally do not agree on the point of the attenuation bias. If the causality is correct there is no attenuation bias, this is what it is. If the causality direction is not correct then it is possible to find an attenuation bias. In other words, the attenuation bias cannot go in both directions.

Ludvigson, Ma, and Ng (2017) - JMCB

A large literature in macroeconomics investigates the relationship between uncertainty and business cycle fluctuations. Interest in this topic has been spurred by a growing body of evidence that uncertainty rises sharply in recessions. But while this evidence substantiates a role for uncertainty in deep recessions, the question of whether uncertainty is an exogenous source of business cycle fluctuations or an endogenous response to economic fundamentals is not fully understood. This paper considers a novel identification strategy to disentangle the causes and consequences of real and financial uncertainty.

Moreover, as surveyed by Ng and Wright (2013), all the post-1982 recessions have origins in financial markets, and these recessions have markedly different features from recessions where financial markets play a passive role. From this perspective, if financial shocks are subject to time-varying volatility, financial market uncertainty - as distinct from real economic uncertainty - could be a key player in recessions, both as a cause and as a propagation mechanism. Contemporaneous changes in uncertainty can arise both as a cause of business cycle fluctuations and as a response to other shocks.

The objective of this paper is to establish a set of stylized facts that addresses these questions econometrically, against which a wide range of individual models could be evaluated. A large literature addresses the question of uncertainty and its relation to economic activity. Theories for which uncertainty plays a key role differ widely on the question of whether this correlation implies that uncertainty is primarily a cause or a consequence of declines in economic activity. In most cases, it is modeled either as a cause or a consequence, but not both. The first strand of literature proposes uncertainty as a cause of lower economic growth. This includes models of real options effects of uncertainty, models in which uncertainty influences financing constraints, or precautionary saving. These theories almost always presume that uncertainty is an exogenous shock to some economic fundamental. A second strand of literature postulates that higher uncertainty arises solely as a response to lower economic growth, emphasizing a variety of mechanisms. Some of these theories suggest that bad times incentivize risky behavior, or reduce information and with it the forecastability of future outcomes, or provoke new and unfamiliar economic policies whose effects are highly uncertain, or create a greater misallocation of capital across sectors, or generate endogenous countercyclical uncertainty in consumption growth because investment is costly to reverse. Finally, a third literature suggests that uncertainty can actually increase economic activity. Growth options theories of uncertainty postulates that a mean-preserving spread risk can cause firms to invest and hire, since the increase in mean-preserving risk increases expected profits. Yet the absence of a theoretical consensus on this matter, along with the huge number of theories and limited body of evidence on the structural elements of specific models, underscore the extent to which the question of cause and effect is fundamentally an empirical matter that must be settled in an econometric framework with as little specific theoretical structure as possible, so that various theoretical possibilities can be nested in empirical tests.

They estimate a reduced form VAR with three variables: macro uncertainty, a measure of real activities, and financial uncertainty. To fully identify the impact matrix they need nine restrictions. Six of them are implicitly provided by the covariance matrix of residuals and three of them should be exogenously imposed. To complete those three missing restrictions they assume to have 2 instruments (one for each type of uncertainty) with the following features. 1. Z_1 is correlated with both types of uncertainty but uncorrelated with real activities. 2. Z_2 is only correlated to financial uncertainty and uncorrelated with the rest. Those two instruments provide the three missing necessary restrictions to just identify the impact matrix. However, they argue that credible external instruments for uncertainty shocks that are truly exogenous may be difficult or impossible to find and defend. Thus, they propose a methodology to construct synthetic proxy variables which should work as instruments.

A theoretical premise of the paper is that structural uncertainty shocks should be reflected in stock prices. They then pretend to be able to run two regressions: 1. stock prices on their past and current first-moment shocks, and 2. stock prices on their past, current first-moment shocks and current macro uncertainty shocks. The residual of the first regression would be Z_1 and the residual of the second would be Z_2 by construction. However, it should be obvious that first-moment shocks and macro uncertainty shocks are not available since they are in function of the three missing identifying restrictions to obtain the rotation impact matrix. This implies that this two-step identification assumption is still underidentified implying that an infinite number of impact matrix would satisfy the system. Thus, they employ two types of winnowing constraints to shrink the number of possible solutions of the impact matrix: 1. the correlation between the first instrument and both types of uncertainty should be above a threshold and the correlation between the second instrument and financial uncertainty should be above to the same threshold as well. 2. financial uncertainty shocks should be above some thresholds in two periods where financial uncertainty was considered to be particularly high and at the same time during the financial crisis the shock to real activities should be negative and below a certain threshold. Hence solutions in the unconstrained set that do not satisfy the lower bounds will be dismissed. They randomly obtain 40000 impact matrices and they only keep the ones which satisfy the constraints above.

Results. In general they consider uncertainty one period ahead. *Financial uncertainty shocks* lead to sharp declines in real activities that persist for many months. These results support that high financial uncertainty is an exogenous impulse that causes declines in real activity. However, financial uncertainty shocks explain few (in terms of variance decomposition) of real activities in the short run, this measure increase over the medium run. *Real activities shocks* have no clear effect on financial uncertainty. Moreover, macro uncertainty increases sharply after a negative real activities shock. So, higher macro uncertainty is an endogenous response to first-moment shocks. Moreover, real activities shocks have a remarkable effect on macro uncertainty in terms of variance explained but explain few of financial uncertainty. *Macro uncertainty shocks* have no effects on financial uncertainty and seem to increase real activities in the short run. Surprisingly, macro uncertainty shocks explain a huge variance of economic activities. Finally their exercise rejects the Choleski identification strategy since no impact matrices have values close to zero on impact.

Stock and Watson (2012) - Brookings Papers EA

The 2007-09 recession and subsequent recovery were qualitatively and quantitatively different from previous postwar recessions. The recession also seems unprecedented in its sources: a financial sector that was unusually vulnerable because of recent deregulation and little-understood derivatives, and a collapse that also dampened the recovery. This paper takes an empirical look at this recession and recovery, with an eye toward quantifying the extend to which this recession differs from previous postwar recessions, the contributions of various shocks to the recession, and the reasons for the slow recovery.

They implement a dynamic factor model. Because a DFM has relatively few factors compared with the number of observed variables, it allows a tractable simultaneous empirical analysis of very many variables in a single, internally consistent framework. The DFM expresses each of the time series as a component driven by the factors, plus an idiosyncratic disturbance term. Moreover, factors are modeled according to a VAR model in function of lag polynomials of the same factors. To estimate the factors they use the first 6 principal components. Principal components span the same space of the factors up to a normalization problem. This arbitrary normalization means that the individual factors do not have a direct economic interpretation. The data set consists of quarterly observations on 200 US macroeconomic time series. They carefully explain how to transform, normalize and detrend them (it can be useful in future). Since the data set contains both high-level aggregates (e.g. consumption) and disaggregated components (e.g. durable and non-durable consumption, services, ...), to avoid double counting, disaggregate components were used to estimate the factors. The DFM is estimated with six factors, a choice consistent with Bai and Ng (2002).

They investigate if the 2007-09 recession exhibited new macrodynamics relative to the 1959Q1-2007Q3 experience. They consider the following experiment: suppose a forecaster in 2007Q3 had in hand their 6 factors and was also magically given a preview of those six factors from 2007Q4 to 2011Q2. Using the pre-2007Q4 model and the post-2007Q3 values of the old factors to predict crisis and post-crisis observables, how well would these predicted values track the actuals over the recession and recovery? In general, the old six factors do a great job to track the 200 observable variables in the data set. They additionally run some tests to rule out any structural break in the macrodynamics. As a result, there is little evidence of a new factor associated with the 2007-09 recession and its aftermath and the response of macro variables to those factors seems to be unchanged. Finally, there were large innovations in these old factors during the recessions. In other words, shocks were larger but still the same.

A second challenge is to obtain an economic interpretation to those innovations, i.e. moving from innovations to structural shocks. This is typically done by first assuming that the innovations can be expressed as linear combinations of the structural shocks, then by imposing economic restrictions that permit identification of the coefficients of those linear combinations. Most identification schemes for structural VAR analysis have an instrumental variables interpretation. Simplest ones use internal instruments in the form of impact or sign restrictions. An alternative method, pioneered by Christina Romer and David Romer (1989) is to use information from outside the VAR to construct exogenous components of specific shocks directly. These exogenous components are typically treated as exogenous shocks; however, technically they are instrumental variables for the shocks: they are not the full shock series, but rather measure an exogenous component of the shock, so that the constructed series is correlated with the shock of interest but not with other shocks. We refer to these constructed series as external instruments, because they use information external to the VAR for identification that is not itself included in the VAR. Suppose one has two instruments that purportedly identify different shocks. If both instruments are valid, then in the population these identified shocks will be uncorrelated. But the population projection does not impose that the two shocks be uncorrelated; in fact, if one or both instruments are not valid, then in general the two shocks will be correlated. They use this last instrumental variable approach for six different structural shocks: oil prices, monetary policy, productivity, uncertainty, liquidity and financial risk, and fiscal policy. They provide a set of important instruments which can be useful in future. In general, a notable correlation is between sources of uncertainty shocks and sources of liquidity/financial risk shocks. The composite uncertainty-liquidity shock attributes approximately twp-thirds of the recession's decline in GDP and employment. Moreover, the contribution of productivity, monetary policy, and fiscal policy shocks are small. Oil shocks contributed to the decline, especially before the financial crisis.

Finally, focusing on the recovery following the 2009Q2 trough, most of the slowness of the recovery is attributable to a long-term slowdown in trend employment growth. The explanation for this declining trend growth rate that we find most compelling rests on changes in underlying demographic factors, primarily in the plateau in the female labor force participation rate and the aging of the workforce. These demographic changes imply continued low or even declining trend growth rates in employment, which in turn suggest that future recessions will be deeper and longer, and will have slower recoveries, than has been the case historically.

Caldara, Fuentes-Albero, Gilchrist, and Zakrajsek (2016) - EER

Empirically distinguishing between financial and uncertainty shocks, however, is difficult because increases in financial market volatility are frequently associated with significant increases in credit spreads. Episodes of acute financial distress are associated with spikes in asset price volatility. Within a SVAR framework this degree of comovement between indicators of financial distress and uncertainty proxies significantly complicates the identification of both shocks - as both types of variables are fast moving. As a result, it is difficult to impose plausible zero contemporaneous restrictions to identify both types of disturbances. It is also difficult to impose sign restrictions on the impulse response functions in order to achieve an economically plausible identification because financial and uncertainty shocks have theoretically the same qualitative effects on both prices and quantities in most instances.

Because there is little consensus among economists on what is the best measure of economic uncertainty, they consider six different proxies: 1. Realized Stock Market Volatility in the spirit of Berger et al. (2019). 2. Option implied volatility as **VXO**. 3. Implied Stock market Volatility from Gilchrist et al. (2014). 4. Macro uncertainty from Jurado et. al (2015) (**JLN**). 5. Policy uncertainty by Baker et al. (2015). 6. Forecast dispersion (disagreement) by Bechman et al. (2013). To measure the tightness of financial market conditions, they rely on corporate bond credit spreads. Specifically, they use the excess bond premium (**EBP**) of Gilchrist and Zakrajsek (2012). They show that the cross-correlations between the EBP and uncertainty proxies are all positiveand tend to be the highest when evaluated contemporaneously. Only exception is for the measure of disagreement which seems to be correlated with some lags to EBP.

They first explore the relative roles of uncertainty and financial conditions as predictors of the near-term of economic activity. In general, the predicted power of EBP seems to be stronger than the one of proxies of economic activities. Indeed, once the state of current financial market conditions is taken into account, it is only the JLN and forecast disagreement uncertainty measures that are informative about the trajectory of economic activities.

To identify uncertainty and financial shocks, they employ the penalty function approach which selects a SVAR model by maximizing a criterion function subject to inequality constraints.[5] In the baseline identification scheme, the first step identifies the uncertainty shocks as an innovation that generates the largest increase in a measure of uncertainty in the first six months. The second step identifies a financial shock which is an innovation that generates the largest increase in the EBP for the first six months and is orthogonal to the uncertainty disturbance identified by the first step. These identifying assumptions do not rule out the possibility that financial conditions might react contemporaneously to a change in economic uncertainty induced by an uncertainty shock; by the same token, macroeconomic uncertainty is allowed to change immediately in response to a financial shock. However, this strategy imposes a timing restriction since the uncertainty shock is identified first and the financial shock has to be orthogonal to it. To take this identification issue into account then they also identify both shocks inverting step 1 with step 2. They acknowledge that neither scheme fully resolves the difficulty problem of how to identify these two types of shocks in a VAR context. They view the two approaches as providing useful bounds on the role of uncertainty and financial shocks in business cycle fluctuations. To implement the two identification schemes, they

[5] The inequality constraints in their case is a non-binding sign restriction that the effect of the two shocks on its own endogenous variable should be always positive.

employ Bayesian estimation techniques. Their monthly VAR specification consists of 10 endogenous variables: 1. Uncertainty proxy; 2. EBP; 3. Industrial production; 4. Employment; 5. Consumption; 6. PCE price deflator; 7. 2-year treasury yield; 8. 10-year treasury yield; 9. Stock market return; 10. Commodity Index from 1975M1:2015:M3 with 6 lags.

Results. Differently to all the other measures of uncertainty, JLN (i) has an hump-shaped response to its own shock and (ii) does not have a significant impact effect on stock prices. All the uncertainty measures lead to a decline in economic activities and a peak on financial conditions. However, once they invert the steps only JLN maintains a significant (although small) effect on financial conditions. In addition, all declines in real activities are smaller and in many cases not significant (JLN is significant). Focusing on JLN and according to which step comes first, uncertainty shocks explain between 20% and 40% of industrial production over the 3 years. Result is specular focusing on financial shocks. Authors conclude that these are evidence that both financial shocks and uncertainty shocks are important independent driver of economic fluctuations. They also show that a large part of this result is driven by the recent outcome of the financial crisis: without that both shocks are less relevant sources of economic fluctuations. Finally, they validate the fact that those shocks are uncorrelated with monetary policy shocks, fiscal shocks, oil shocks and unexpected TFP shocks. Correlation is low but it is difficult to say how much relevant they can be if controlling for all of them. Moreover, unexpected TFP shocks are correlated to negative 16.