The Information Economy: Old Themes and New Directions in Macroeconomics and Finance

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"Data is to this century, what oil was to the last one," proclamed the Economist in 2017. Data, or digitized information, is more central to finance and to the aggregate economy than ever before. Firms are more data-focused, trading strategies are more data-intensive, and the old manufacturing-based models of economic output are ripe for replacement with tools that reflect the new knowledge economy. The modern economy is an information economy. Understanding what information agents see and how that information impacts aggregate outcomes is a central challenge.

Information and beliefs play a role in every model and every economic choice. Many times, these beliefs are in the background. Full-information rational expectations, meaning full knowledge of the true distribution of shocks and the complete, global history of all actions, is a standard assumption. But in some cases, rational expectations may prevent us from understanding aggregate phenomena.

One difficulty of studying information frictions is that information is often not measurable. A key contribution of modern information theories has been to use theory to map data into beliefs. For example, we have developed simple tools that are compatible with modern DSGE models and calibration methods, used information choice to infer information from observable states, and mapped data flows in bytes to information precisions. These techniques leverage ever-growing data to learn about information.

The tools described below have been applied to many topics, including: business cycles, portfolio choice, labor, leadership, auctions, financial intermediation, social networks and economic growth. Many of these applications are described in my textbook, Information Choice in Macroeconomics and Finance (Veldkamp, 2011)[1]. Instead of grouping work by its topic, I describe a few type of the mechanisms and how they have been used in various contexts.[2]

1 Information as a By-Product of Economic Activity

One of the ways people learn is by observing outcomes. We see firms grow or fail. We see unemployment rise or fall. This information shapes our view of the risks we face, the state of the economy, and the wisdom of risky investment.

My first two papers (Veldkamp, 2005; Van Nieuwerburgh and Veldkamp, 2006b) used this idea to explain the asymmetry in asset prices and business cycles by connecting information flow and uncertainty to the level of economic activity. In booms, ample economic activity produces abundant information and reduces uncertainty. When a boom turns to a slump, a large data set alerts investors to the change with

[1] 3000+ copies sold

[2] This is not even close to a comprehensive survey of these topics. I apologize sincerely to those whose work I have not included. This is only a sampling of work mostly closely related to my own interests that I could assemble with limited time.

high degree of accuracy; investors respond decisively. In a slump, less economic activity generates less information. If the economy improves, the uncertainty arising from a lack of data slows investor reactions, making the boom more gradual. As in Bloom (2009), the paper documents the rise in uncertainty in recessions. Other authors (Fajgelbaum et al., 2014; Mäkinen and Ohl, 2015; Ordoñez, 2013) used a similar mechanism to explain emerging market crashes, secular stagnation and asset pricing facts. All use the idea that information is tied to aggregate economic activity to infer information quality from macro outcomes. Because observable data implies information, which in turn, predicts observable actions, these theories are testable and have been supported by U.S., international, and global financial data.

Fogli and Veldkamp (2011) uses the mechanism of learning from economic activity to explore economic geography. One of the largest transformations of the economy over the last century was the rise of female labor force participation. But this transformation took place at different times in different locations. In the model, women learn about the effects of maternal labor force participation on children from observing other women who work outside the home. Calibrated to county-level participation rates at the start of the twentieth century, the model produces geographical trends that match U.S. county-level participation data, along many dimensions.

2 Putting Econometricians in Models: Uncertainty and Tail Risk

A new turn in this line of research is putting econometricians in models. Intuitively, most people think that observing economic events can change beliefs. For example, the financial crisis caused many to revise their estimated probability of future collapse. This change in beliefs probably has substantial economic consequences. But the challenge is that it is hard to quantify. Putting econometricians in models is a way of using aggregate data to estimate belief distributions. This line of work is similar to many of the ideas of Hansen and Sargent (Hansen and Sargent, 2001, 2008, 2010). But instead of twisting preferences to make agents fear model misspecification, these theories feature agents who have standard preferences and use classical or Bayesian econometrics to estimate unknown parameters or distributions.

Many recent theories in finance and economics use "uncertainty shocks to create realistic fluctuations (Christiano et al., 2014). Others use shocks to tail risk (Wachter, 2013; Gabaix, 2012). But these theories do not tell us why uncertainty or tail risk fluctuates so much. Uncertainty is not an exogenous feature of an environment. It is expected squared forecast error, based on an information set and a model. Orlik and Veldkamp (2014) and Orlik, Veldkamp, and Kozeniauskas (2013) use econometricians in models to explain fluctuations in various types of economic uncertainty. The agents in these models use U.S. macro time series to form Bayesian estimates of the distribution from which the data come. New pieces of data cause agents to re-estimate the distribution, in particular, its skewness. Because skewness and tail probabilities are difficult to estimate, their estimates are very sensitive to new data. Thus, a simple Bayesian forecaster experiences large fluctuations in estimated tail risk and uncertainty, which can trigger sizable aggregate fluctuations.

Kozlowski, Veldkamp, and Venkateswaran (2017) argues that when agents are econometricians, a new source of persistence can arise, in response to tail events. The paper uses this insight to argue that observing the financial crises permanently changed the beliefs of market participants about what kinds of events are possible in the U.S. economy. It starts from the premise that no one knows the true distribution of shocks. We estimate a distribution, given available data. For events that are frequently observed, our probability estimates are good and new events have little effect on those estimates. But for rarely observed, tail events, data is scarce. A new observation of a tail event significantly changes the probability we assign to that event. Even if the event itself is transitory, the data corresponding to that event stays in our data set forever after. The rise in estimated tail risk persistently depresses output, for years to come. This same mechanism offers an explanation for persistently low riskless rates Kozlowski, Veldkamp, and Venkateswaran (2018).

3 Information Choice

A sequence of papers examines the choice of an investor who can first allocate a limited amount of capacity (or time) to learn about a set of risky assets and must then choose a portfolio of assets to purchase. Van Nieuwerburgh and Veldkamp (2010) shows how gains to specialization arise. Specialization in learning about a small set of assets causes investors to over-weight those assets, and under-diversify, relative to what a standard portfolio model would predict. Because investors are ex-ante identical, this model cannot predict who learns what. To connect information choice to investor characteristics, Van Nieuwerburgh and Veldkamp (2009) investigates a two-country setting where there are small initial differences in agents' information sets. Because investors prefer to learn more about risks that others know less about, learning amplifies the initial information asymmetries. Jointly analyzing information and investment choice provides explanations for a broad set of facts relating to patterns of foreign investment, own-company stock bias (Van Nieuwerburgh and Veldkamp, 2006a), and excess returns on locally-biased portfolios, all within a fully rational, general equilibrium framework.

Of course, investors do not always process their own information. Investing in a fund is a way of purchasing information processing services from experts. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) and Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) explore the problem of a fund manager who must choose what assets to research and invest. We used mutual fund data to corroborate subtle features of the rational information choice model that distinguish it from other alternatives. This model generalized the choice problem of the earlier models by expanding the types of risks agents can learn about. The framework developed in these papers has been used to explain many phenomena, including income inequality (Kacperczyk et al., 2015), trading strategies (Abis, 2017), international investment (Valchev, 2017), and return predictability (Andrei and Hasler, 2016).

These models use tools from rational inattention (Sims, 2003, 2006) to model the information choice problem. In that respect, these models are closely connected to other rational inattention theories such as, price-setting (Maćkowiak and Wiederholt, 2009), consumption (Matejka and McKay, 2015), and household finance (Andersen et al., 2015).

4 Markets for Information

A special case of information choice arises when agents choose to purchase information from a market with a competitive price. Because of its high fixed cost, information that few people purchase is expensive; information sold to many is cheap. The low price encourages investors to buy information that many others also buy. Investors who observe the same information will want to buy and sell the same assets. Veldkamp (2006b) and Veldkamp (2006a) use markets for information to explain asset market frenzies and asset price comovement. Asset market frenzies and asset price comovement both bear the hallmarks of coordination games: investors seem to want to buy at the same time and acquire the same assets as other investors. Many papers have altered preferences, investment constraints or shock distributions to generate complementarity. Non-convexity in information production naturally generates the requisite complementarity.

Veldkamp and Wolfers (2007) offers a new potential answer to an old question: Why does the output of diverse industries covary so much? Information markets in that model induce firms to acquire aggregate productivity information, which is cheap, rather than firm-specific productivity information, which is expensive. Firms that observe aggregate information make similar decisions, even though their true productivity shocks are not highly correlated.

5 Private vs. Public Information: Global Games and Auctions

In the models of information markets and information choice, externalities make learning strategic. For example, in the portfolio models, investing is a strategic substitute - if many others want to buy an asset, its price rises and its return falls. Since agents don't want to buy assets others will invest in, they don't want to learn information that others will know. This is why investors don't specialize in the same assets and don't hold the same portfolios. To better understand the general connection between the strategic motives in actions and in information acquisition, Hellwig and Veldkamp (2009) examines information acquisition in a Morris and Shin (2002)-style strategic game. We find that the strategic motives in action games are systematically passed on to the information choices, but the uniqueness and dynamics of equilibria change. Myatt and Wallace (2012) and Cornand and Heinemann (2008) moderated some of these results by considering different types of public and private signals.

Treasury auctions have been the subject of recent scandals. Justice officials are investigating whether primary dealers have been sharing information about clients' orders, ahead of the auction. But information sharing in treasury auctions has been pervasive for years. Boyarchenko, Lucca, and Veldkamp (2016) explores who gains and who loses when dealers share order flow information with clients and with each other. Using a framework with risky correlated values, this paper offers a new approach to estimating auctions for financial assets.

6 New Directions: Information Models of Big Data

New data technologies are pervasive and transformative. The Economist declares data to be "the new oil," and new financial trading strategies are devised daily to extract others' data. While empirical economists have dug in to exploit big data for measurement, most theory has not kept pace with this new reality. Data is information. As in Farboodi, Matray, and Veldkamp (2017), frameworks designed to examine information scarcity can be inverted to measure and predict the effects of growing information abundance.

Farboodi and Veldkamp (2017) argue that when information technology, or FinTech, becomes more productive, investors switch from processing fundamental data about asset payoffs, to processing data about others' demands. This switch in information prompts in a change in trading strategies that resembles recent market trends. Making this argument requires extending the information choice and portfolio choice framework in a new direction: Not only do investors choose what assets or risks to learn about, they choose what type of information – fundamental or order-flow – to learn.

Begenau, Farboodi, and Veldkamp (2017) argue that big data can explain recent macroeconomic trends. Davis and Haltiwanger (2015) document that while small firms have struggled, large firms (> 1000 employees) have thrived: The share of the U.S. labor force they employ has risen from one quarter in the 1980s, to about a third today. Larger, older firms have a longer data history. That makes them easier to evaluate, easier to predict and thus cheaper to fund. Work in progress considers how firms use their own data on customer transactions to provide more valuable goods and services and to grow. Since firm growth generates more sales, more data and more growth, big data could well be a new source of increasing returns to scale.

Information, information technology, and big data are key inputs to and outputs of modern economic activity. Adapting traditional frameworks to this new reality is not an easy task. Aggregate theories featuring a role for information are slowly advancing to embrace this challenge.

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