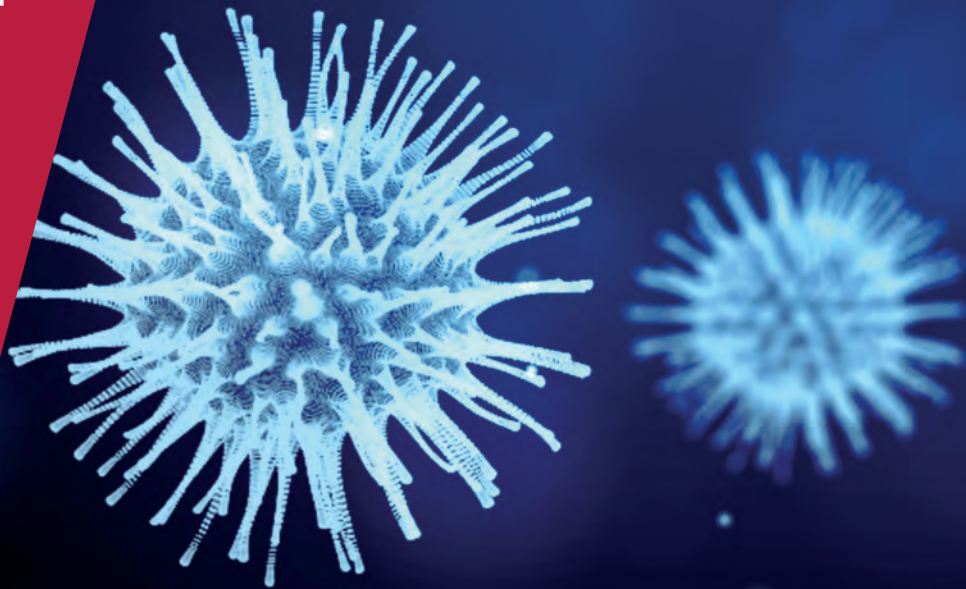


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Real-time real economic activity entering the pandemic recession¹

Francis X. Diebold²

Date submitted: 15 December 2020; Date accepted: 16 December 2020

Entering the Pandemic Recession, we study the high-frequency real-activity signals provided by a leading nowcast, the ADS Index of Business Conditions produced and released in real time by the Federal Reserve Bank of Philadelphia. We track the evolution of real-time vintage beliefs and compare them to a later-vintage chronology. Real-time ADS plunges and then swings as its underlying economic indicators swing, but the ADS paths quickly converge to indicate a return to brisk positive growth by mid-May. We show, moreover, that the daily real activity path was extremely highly correlated with the daily COVID-19 path. Finally, we provide a comparative assessment of the real-time ADS signals provided when exiting the Great Recession.

- ¹ For helpful discussion I thank Boragan Aruoba, Scott Brave, Andrew Patton, Glenn Rudebusch, Frank Schorfthide, Chiara Scotti, Minchul Shin, Keith Sill, Mark Watson, Tom Stark, Jim Stock, Herman van Dijk, and Simon van Norden. I am also grateful to conference/seminar participants at the Federal Reserve Bank of Philadelphia, the Society for Financial Econometrics, Amazon, the Department of Statistics at the Wharton School, and the International Association for Applied Econometrics. For outstanding research assistance and related discussion I thank Philippe Goulet Coulombe, Tony Liu, and Boyan Zhang. The usual disclaimer applies.
- ² Paul F. Miller, Jr. and E. Warren Shafer Miller Professor of Social Sciences, and Professor of Economics, Finance, and Statistics, University of Pennsylvania.

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1 Introduction

Accurate assessment of current real economic activity (“business conditions”) is key for successful decision making in business, finance, and policy. It is difficult, however, to track business conditions in real time, both because no single observed economic indicator *is* “business conditions”, and because different indicators are available at different observational frequencies, and with different release delays. Nevertheless there exists the tantalizing possibility of accurate real-time business conditions assessment (“nowcasting”), and recent decades have witnessed great interest in nowcasting methods and applications (e.g., Banbura et al. (2011)).

The workhorse nowcasting approaches involve dynamic factor models, which relate a set of observed real activity indicators to a single underlying latent real activity factor. Both “small data” approaches (e.g., based on 5 indicators) and “Big Data” approaches (e.g., based on 500 indicators) are available. Small data approaches were developed first, and they typically involve maximum likelihood estimation (e.g., Stock and Watson (1989)). Subsequent Big Data approaches, in contrast, typically involve two-step estimation based on a first-step extraction of principal components (e.g., Stock and Watson (2002), McCracken and Ng (2016)).

Both introspection and experience reveal that Big Data nowcasting approaches are not necessarily better. First, they are more tedious to manage, and less transparent. Second, they may not deliver much improvement in factor extraction accuracy, which increases and stabilizes quickly as the number of indicators increases (Doz et al., 2012). Third, casual inclusion of many indicators can be problematic because a poorly-balanced set of indicators can create distortions in the extracted factor (Boivin and Ng, 2006), whereas small data approaches promote and facilitate hard thinking about a well-balanced set of indicators (Bai and Ng (2008)).

Against this background, in this paper we assess the performance of a leading small-data nowcast, the Aruoba-Diebold-Scotti (ADS) Index of Business Conditions (Aruoba et al., 2009). ADS is designed to track real business conditions at high frequency, and it has been maintained and released in real time by the Federal Reserve Bank of Philadelphia continuously since 2008.¹ Its modeling style and underlying economic indicators build on classic

¹The production version used by FRB Philadelphia differs in some ways (e.g., included indicators and treatment of trend) from the prototypes provided by Aruoba et al. (2009) and Aruoba and Diebold (2010), which themselves differ slightly. All discussion in this paper refers to the FRB Philadelphia version. All materials, including the full set of vintage nowcasts, are available at <https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index>.

early work in the tradition of Burns and Mitchell (1946), Sargent and Sims (1977), and Stock and Watson (1989). The underlying indicators span high- and low-frequency information on real economic flows: weekly initial jobless claims; monthly payroll employment growth, industrial production growth, personal income less transfer payments growth, manufacturing and trade sales growth; and quarterly real GDP growth.

Crucially, we assess ADS using only information actually available in real time. This is required for truly credible real-time evaluation, and it can only be achieved by using nowcasts produced and permanently recorded in real time, which is very different from simply removing final-revised data and inserting vintage data into an otherwise ex post analysis. Unfortunately, such evaluations are rare, because there simply are not many instances of long series of nowcasts produced and recorded in real time. ADS, however, has been produced and recorded in real time roughly twice weekly since late 2008, so we can provide real-time performance assessments both exiting the Great Recession and entering the Pandemic Recession.

We proceed as follows. In section 2 we provide background on aspects of ADS construction, updating, ex post characteristics, and performance evaluation. In section 3 we examine ADS entering the Pandemic Recession, and we relate the real-time ADS path to the real-time COVID-19 path. In section 4 we provide a comparative examination of ADS exiting the Great Recession. We conclude in section 5.

2 Nowcast Construction, Characteristics, and Assessment

Here we provide background on the ADS index construction (section 2.1), ex post historical characteristics (section 2.2), and general issues of relevance to assessing ex ante nowcasting performance (section 2.3).

2.1 Construction and Updating

ADS is a dynamic factor model with multiple mixed-frequency real activity indicators driven by a single latent real activity factor. The ADS index is an estimate of that latent real activity factor. Importantly, the model is specified such that *the real activity factor tracks the de-meaned growth rate of real activity*. Progressively more negative or positive values indicate progressively worse- or better-than-average real growth, respectively. Because ADS tracks

real activity growth, not level, a positive value does not necessarily mean “good times”; rather, it means “good growth”, which may be from a level well below trend, as for example in the early stages of a recovery.

ADS is specified at daily frequency, allowing as necessary for missing data for the less-frequently observed variables.² Importantly, despite complications from missing data, time-varying system matrices, aggregation across frequencies, etc., the Kalman filter and associated Gaussian pseudo likelihood evaluation via prediction-error decomposition remain valid, subject to some well-known modifications.³ Model estimation is therefore straightforward, after which the Kalman smoother produces an optimal extraction of the underlying real activity factor. That is, the Kalman smoother produces the ADS index: The extracted sequence at any time t^* is the vintage- t^* ADS sequence, $\{ADS_1, ADS_2, \dots, ADS_{t^*}\}$.

The first ADS vintage was released 12/5/2008, covering 3/1/1960 through 11/30/2008. Since then, ADS has been continuously updated whenever new data are released. The Kalman smoother is re-run, generally within two hours of the release, and the newly-extracted index from 3/1/1960 to “the present” is re-written to the web. ADS has been updated approximately eight times per month on average since inception.

2.2 Ex Post Characteristics

In Figure 1 we show the ADS index from 03/01/1960 through 12/31/2013, as assessed in the 6/26/2020 vintage. The sample range is well before the vintage pull date, so the chronology displayed is (intentionally) ex post. We do this because it is instructive to examine the ex post chronology before passing to real time assessment, which can only be done after ADS went live in late 2008.⁴

Several features are noteworthy. For example, the ADS chronology coheres strongly with the NBER chronology, plunging during NBER recessions. In addition, several often-discussed features of the business-cycle are evident in ADS, such as the pronounced moderation in volatility during the Greenspan era.

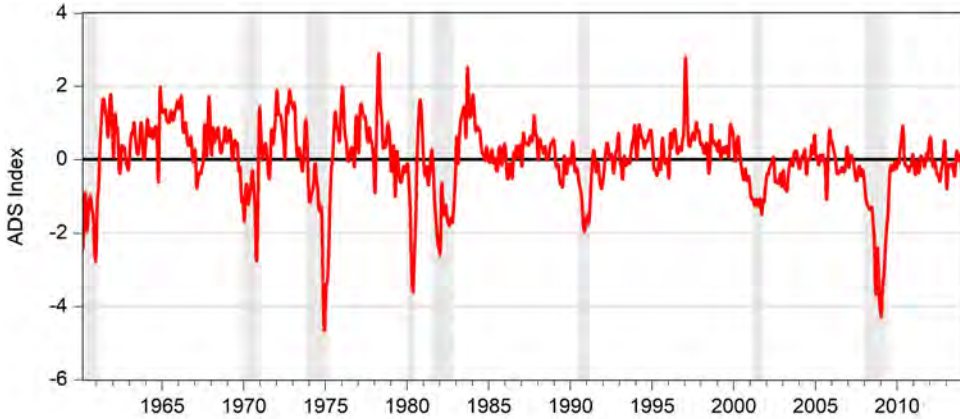
The ADS value added relative to the NBER chronology stems from the facts that (1) it is a cardinal measure, allowing one to assess not only recession durations, but also depths and

²The model must be specified at daily frequency, despite the fact that the highest-frequency indicator is weekly initial jobless claims, to account for the varying number of days/weeks per month, which also produces time-varying system parameter matrices.

³See, for example, Durbin and Koopman (2001) on missing data, and Harvey (1991) on aggregation of flow variables.

⁴The sample period intentionally excludes the Pandemic Recession, which we will subsequently examine in detail.

Figure 1: ADS Index: Ex Post Path 03/01/1960 - 12/31/2013 (Vintage 6/26/2020)



Notes: The shaded regions are NBER-designated recessions.

patterns (see Table 1), and (2) its updates arrive in timely fashion, whereas the starting and ending dates NBER recessions are typically not announced until well after the fact (again see Table 1). Of course, if ADS is to be a useful guide for business and policy decisions, its frequently-arriving updates must provide reliable signals in real time, not just ex post as in Figure 1. We now turn to that issue.

2.3 Performance Assessment

Truly credible nowcasting performance assessment requires using *vintage information*, which emerges as the limit of a sequence of progressively more realistic and credible nowcast/forecast evaluation approaches:⁵

- (1) Use full-sample estimation, and use final revised data
- (2) Use expanding-sample estimation, and use final revised data
- (3) Use expanding-sample estimation, and use vintage data (“Pseudo Real Time”)
- (4) Use expanding-sample estimation, and use vintage information (“Real Time”).

⁵Note that nowcasts are effectively just h -step-ahead forecasts with horizon $h=0$.

Table 1: NBER Recessions

Recession Dates		Recession Characteristics		
Peak Month	Trough Month	Duration	Depth	Severity
April 1960	February 1961	10	2.7	27.0
December 1969	November 1970	11	2.8	30.8
November 1973	March 1975	16	4.7	75.2
January 1980 (6/3/1980)	July 1980 (7/8/1981)	6	3.6	21.6
July 1981 (1/6/1982)	November 1982 (7/8/1983)	16	2.9	46.4
July 1990 (4/25/1991)	March 1991 (12/22/1992)	8	1.7	13.6
March 2001 (11/26/2001)	November 2001 (7/17/2003)	8	1.5	12.0
December 2007 (12/1/2008)	June 2009 (9/20/2010)	18	4.3	77.4
February 2020 (6/6/2020)	?	?	?	?

Notes: Recession dates and durations in months are from the NBER chronology; see <https://www.nber.org/cycles.html>. When available, the announcement dates appear in parentheses. The NBER trough month for the Pandemic Recession has not yet been announced. Recession depth is the minimum absolute daily ADS value during the recession; more precisely, the depth D of recession R is $D = \min_i(ADS_i)$, $i \in R$, where i denotes days. Recession severity S is the product of depth and duration. Both D and S use a late-vintage ADS chronology and the NBER recession chronology.

Approaches (1) and (2) are clearly unsatisfactory: Approach (1) uses time periods and data values not available in real time, and approach (2) is an improvement but still uses data values not available in real time. Approach (3), involving vintage *data*, is typically viewed as the gold standard. It is implemented comparatively infrequently, however, due to the tedium involved and the fact that vintage data are often unavailable.⁶ Approach (4), involving vintage *information*, limits the information set to that available and actually used in real time, which is more restrictive than merely limiting the *data* to that available in real time. It is, however, almost never implemented.

To appreciate why fully-credible assessment requires vintage information rather than just vintage data, consider the following:

- (1) Econometric/statistical theory and experience evolve, prompting changes to the estimation procedure; the frequency and timing of re-estimation and its interaction with benchmark revisions; the estimation sample period; allowance for parameter variation

⁶The two key sources of U.S. vintage data are the Real-Time Dataset for Macroeconomists at the Federal Reserve Bank of Philadelphia (<https://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/>), and ALFRED at the Federal Reserve Bank of St. Louis (<https://alfred.stlouisfed.org/>).

and breaks; the treatment of outliers; the strength of regularization employed; the predictive loss function employed; etc.

- (2) Economic theory and empirical economic experience evolve. Over time this may prompt, for example, the removal or re-weighting of some component nowcast indicators and/or addition of others (e.g., Diebold and Rudebusch (1991)), as well as deeper changes in the nowcasting model.
- (3) Exact times and reliability of nowcast/forecast calculation and release may differ due to technological problems; outright mistakes in nowcast/forecast construction; evolving or changing software algorithms and associated bugs; parallel problems at the agencies responsible for the underlying data and decisions regarding how to deal with them in forecast/nowcast construction; etc.

For these and other reasons, just as truly credible evaluation requires refraining from endowing agents with better data than were actually available in real time, so too does it require refraining from endowing them with better economic or statistical models and related tools than were actually available in real time, better judgment and decision-making abilities/choices than were actually manifest in real time, etc.

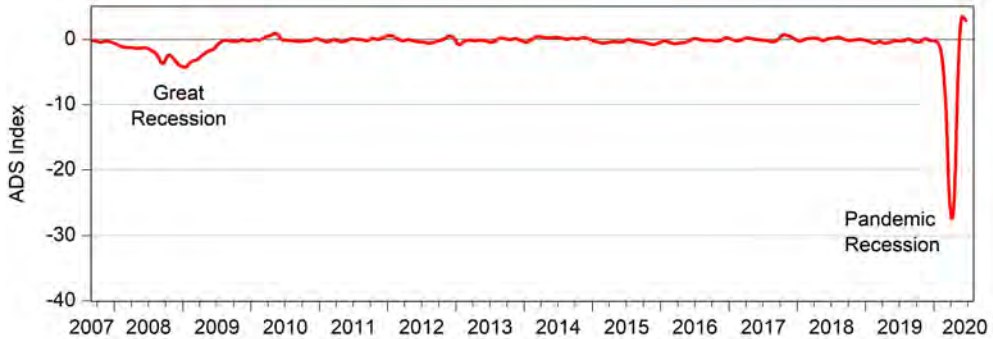
The upshot is clear: Truly credible real-time evaluation – that is, evaluation using vintage information rather than just vintage data – can only be obtained by using nowcasts produced and permanently recorded in real time. ADS has been produced and recorded in real time since late 2008, so we can credibly study the key episode of current interest, entry into the Pandemic Recession. We now proceed to do so.

3 The Pandemic Recession Entry

We focus in this section on the Pandemic Recession that started in March 2020. It is instructive to begin by comparing it to the Great Recession of 2007-2009. To that end we show the ADS path in Figure 2, from late 2007 through June 2020.⁷ The so-called “Great Recession” appears minor by comparison.

⁷We refer to an ADS extraction as a path.

Figure 2: ADS Index: Ex Post Path 12/1/2007 - 6/26/2020 (Vintage 6/26/2020)



3.1 A Detailed Look at the Later-Vintage Path

Figure 2 reveals the jaw-dropping ADS drop in the Pandemic Recession, more than five times that of any other recession since 1960. The ADS drop is entirely appropriate, due to similarly jaw-dropping and historically unprecedented movements in its underlying indicators.

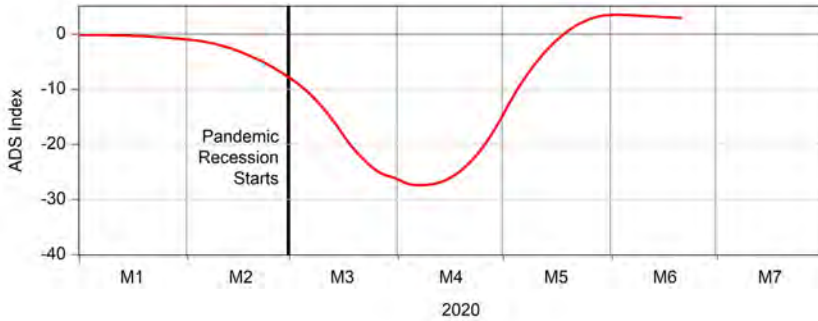
As of this writing, the official trough month for the Pandemic Recession has not been announced. It could be as early as May 2020, in which case the Pandemic Recession would be the shortest in history. Indeed a May trough turns out to be likely. In Figure 3 we show the later-vintage Pandemic Recession path. The overall extracted path is smooth and convex, with a minimum in early April, and a return to positive growth by mid-May. We emphasize again, however, that ADS measures real activity growth, not level. Hence positive ADS does not necessarily mean “good times”; rather, it means “good growth”, which may be from a very bad initial condition. That was the situation in late May, as the battered U.S. economy evidently resumed growth.

3.2 Real-Time Vintages

3.2.1 Five Snapshots

In Figure 4 we show several end-of-month paths in black, starting with February 2020. For comparison, in each panel we also show the later-vintage path in red. Moving through the five panels of Figure 4:

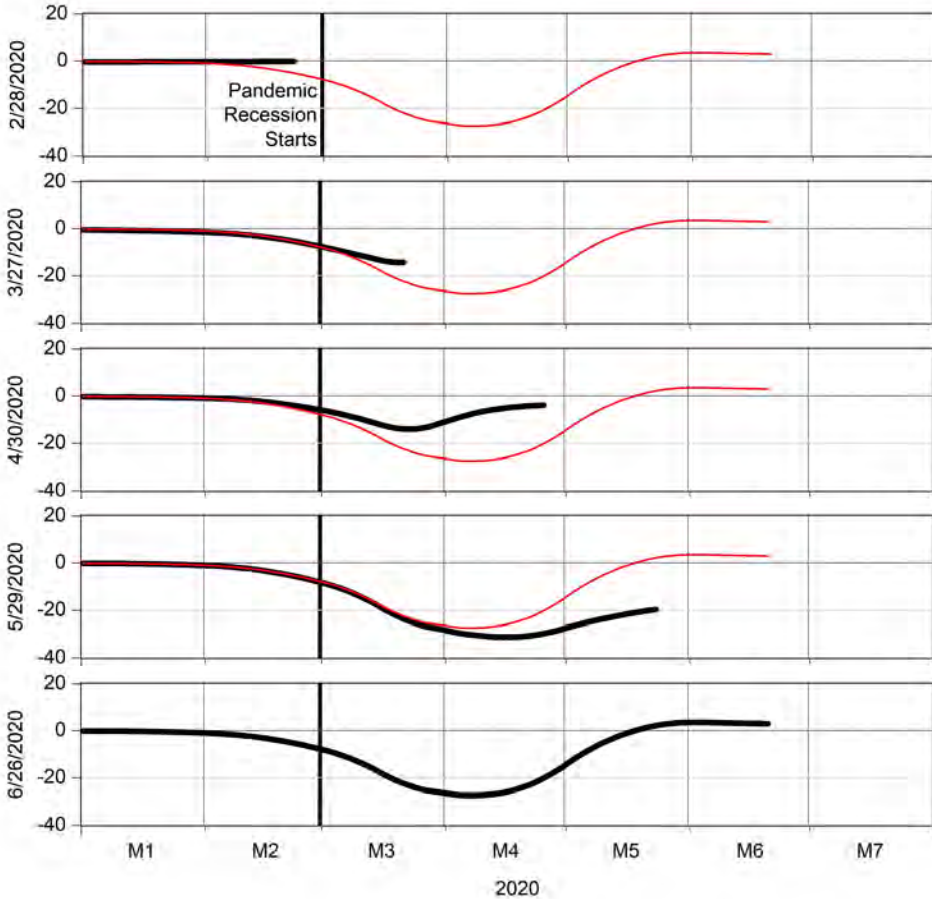
Figure 3: ADS Index: Ex Post Path 1/1/2020 - 6/26/2020 (Vintage 6/26/2020)



- (1) In the top panel we show the 2/28/2020 path. ADS has not moved.
- (2) In the second panel we show the 3/27/2020 path, which looks very different. ADS has become acutely aware of the disastrous situation; indeed most of the 3/27 path is well below the previous all-time (post-1960) ADS low during the 1970s oil-shock recession.⁸
- (3) In the third panel we show the 4/30/2020 path. The April initial claims news is bad, but less bad than March, which is good, and ADS shows a minimum in late March followed by a rise toward normalcy by the end of April.
- (4) In the fourth panel we show the 5/29/2020 path. The May news is very bad, dominated by the shockingly bad May 8 payroll employment number (for April), and the late-May path is massively down-shifted relative to the late-April path. The new minimum is in mid-April rather than late March, and the 5/29 ADS value is thoroughly dismal, nowhere near normalcy.
- (5) In the fifth panel we show the 6/26/2020 path. Thanks to the strong May payroll employment number (released June 5), ADS moved into normal territory, and stayed there. There is clear (albeit highly-tentative evidence for a Pandemic Recession trough in mid-May, when ADS hits 0.)

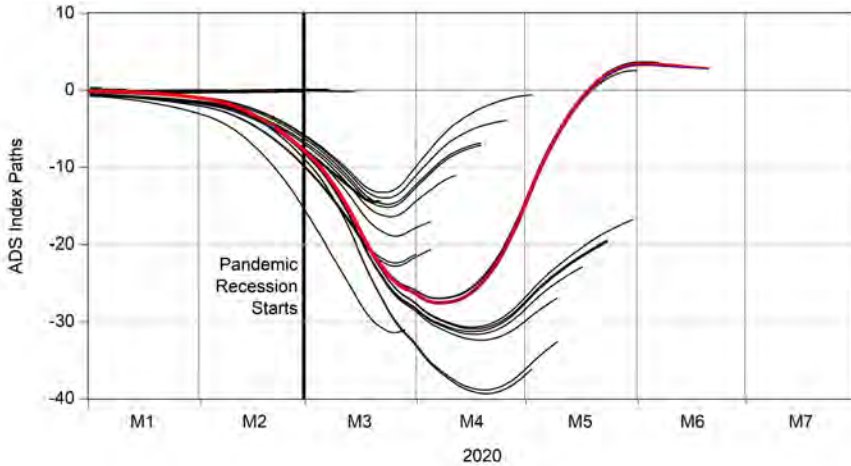
⁸It is also apparent that the Kalman smoother may be smoothing “too much”, producing low ADS values well before mid-March, going back into February and even January. Its smoothing is optimal relative to the patterns in historical data, but the March initial jobless claims movements were unprecedentedly sharp.

Figure 4: Entering the Pandemic Recession: Monthly Real-Time ADS Paths



Notes: We show five monthly real-time ADS paths in black. From top to bottom they are 2/28/2020, 3/27/2020, 4/30/2020, 5/29/2020, and 6/26/2020. For comparison we show the 6/26/2020 path in red in all panels. (In the bottom panel, we show only black, since black and red are identical.)

Figure 5: Entering the Pandemic Recession: Real Time ADS Path Plot



Notes: We show all real-time ADS paths in black, through 6/26/2020. For comparison we show the complete later-vintage path (6/26/2020) in red.

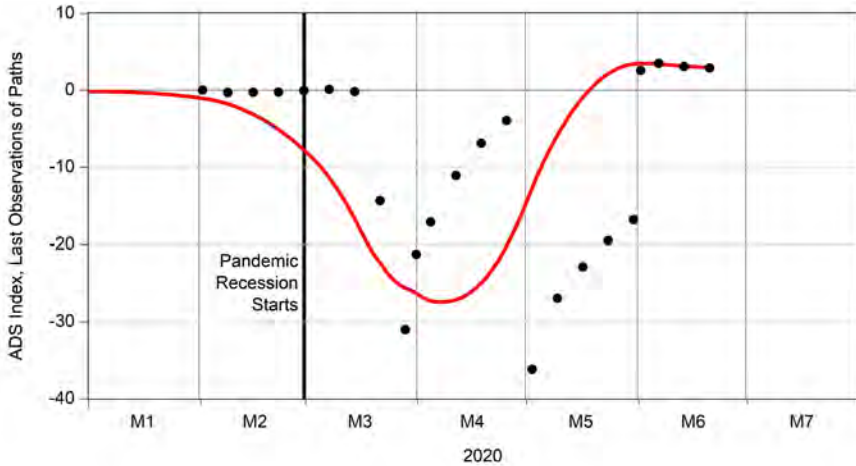
3.2.2 The Full Path Plot and Dot Plot

In Figure 5 we show the complete path plot during the Pandemic Recession through 6/26/2020, with the later-vintage path in red for comparison. The path plot is the set of all real-time paths; by following rightward through the sequence of paths, moving through time, we track the evolution of ADS beliefs about the chronology of business conditions.

There are wide real-time divergences between individual early paths and the later vintage red path. There are interesting patterns, however, with several real-time “meta paths” evident:

- (1) The first extends through the 3/19/2020 ADS announcement. ADS does not move. Initial claims rise from 0.2m to 0.3m, a large move by historical standards, confirming what everyone already knew: the pandemic would have important real economic consequences, but the Kalman smoother optimally but erroneously ascribes it to measurement error.
- (2) The second meta-path begins with the 3/26/2020 and 4/2/2020 initial claims explosions. ADS plunges, but then recovers steadily despite a steady stream of bad news

Figure 6: Entering the Pandemic Recession: Real-Time ADS Dot Plot



Notes: We show the last values of all real-time ADS paths in black. For comparison we show the complete later-vintage path (6/26/2020) in red.

(it is bad, but getting less bad), almost back to 0 by the 5/7/2020 initial claims announcement.

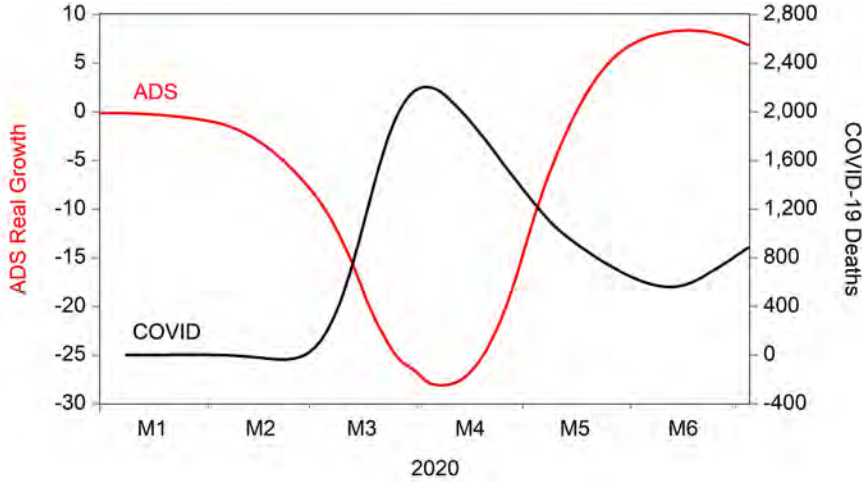
- (3) The third meta-path begins with the horrific 5/8/2020 April payroll employment release, with ADS again plunging. It then again begins mean reverting, and does so completely when the strong May payroll employment number is released on 6/5/2020.

In Figure 6 we show the corresponding “dot plot”, with the 6/26/2020 path again superimposed. Each dot is the last observation of its corresponding path in Figure 5. The dots are real-time filtered values, because smoothed and filtered values coincide for the last observation in a sample. The dot plot is highly volatile and emphasizes the various meta-paths.

3.3 Real Economic Activity and COVID-19

Because the March-April 2020 collapse in economic activity was obviously caused by COVID-19, it is of interest to directly examine the correlation between the two. We can do so at high frequency (daily), because we have both daily ADS and COVID new cases / deaths data. We want to correlate COVID new cases with ADS, but the direct new cases data are less reliable

Figure 7: Daily ADS and Smoothed Daily COVID-19 Deaths



Notes: We show ADS (6/26/2020 vintage) vs HP-filtered daily COVID-19 deaths led by 20 days. See text for details.

than deaths during the period of interest, because new cases were likely heavily influenced by changes in the amount of testing undertaken. Instead, a more reliable indicator of new cases is deaths, adjusted for the approximate 20-day period between infection and death. Hence we use deaths led by 20 days.⁹ In Figure 7 we show ADS vs COVID deaths+20.¹⁰ The strength of the negative correlation is striking. Of course economic activity plunged in March when COVID exploded, but there’s much more than that – ADS and COVID continue to move in lockstep (inversely) through the April COVID peak, its April-May decline, and its June rebound.

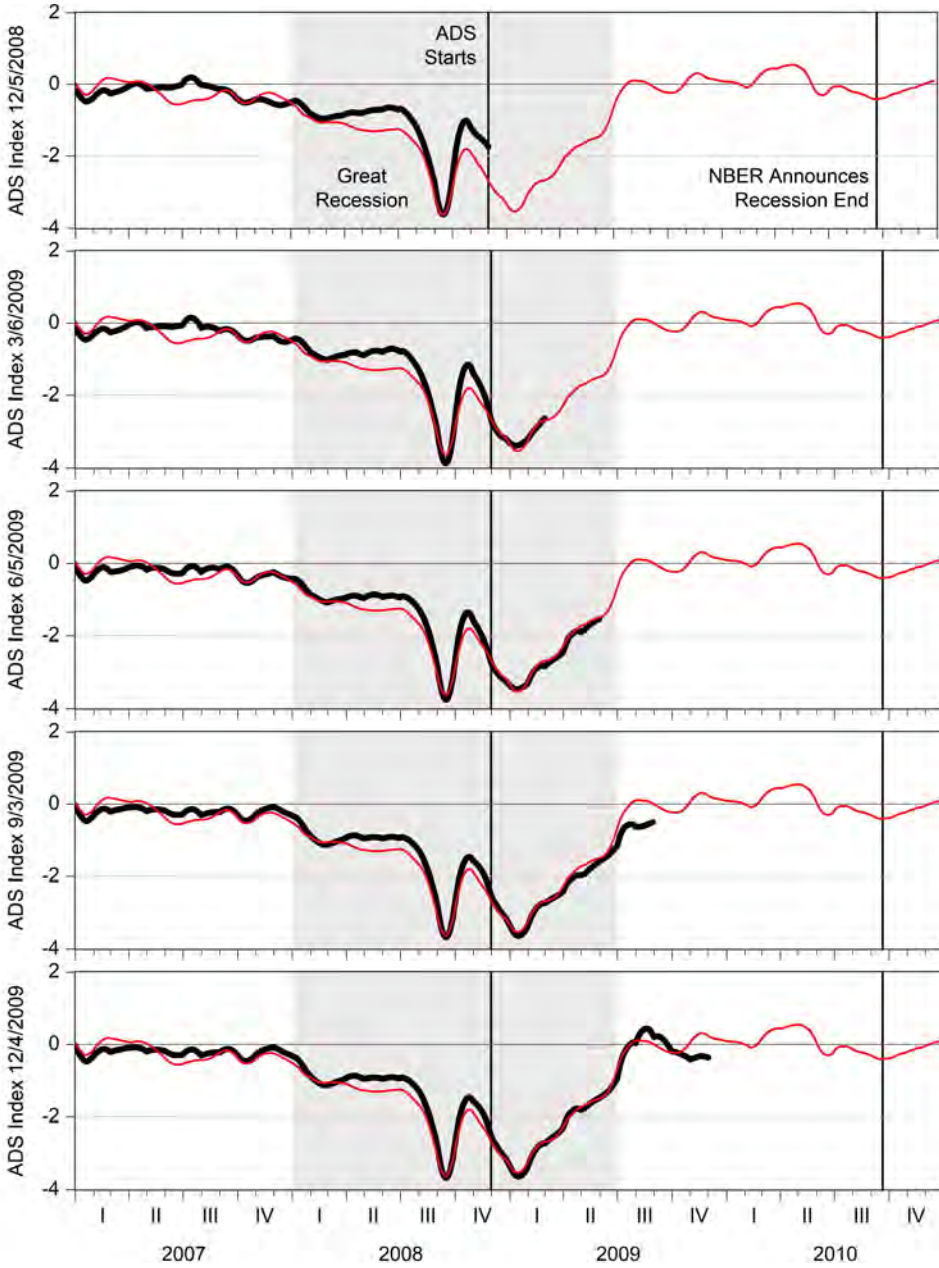
4 Comparison to the Great Recession Exit

It is informative to compare the evolution and congealing of views during the Pandemic Recession entry to those during an earlier, more “standard”, recession, like the Great Re-

⁹We use the Johns Hopkins University CSSE COVID-19 daily deaths data; see Dong et al. (2020) and <https://github.com/CSSEGISandData/COVID-19>.

¹⁰We also smooth COVID deaths+20 using a Hodrick-Prescott filter to remove the strong calendar effects in recorded deaths.

Figure 8: Exiting the Great Recession: Five Quarterly Real-Time ADS Paths



Notes: We show five quarterly real-time ADS paths in black. From top to bottom they are 12/5/2008, 3/6/2009, 6/5/2009, 9/3/2009, 12/4/2009. For comparison we show a later-vintage ADS path (December 2010) in red.

cession of 2007-2009. We can't examine real-time ADS when entering the Great Recession, because ADS did not start until December 2008, well after the great recession began. But we can examine it when *exiting* the great recession. In Figure 8 we show five paths in black, from ADS inception through the end of the Great Recession, at quarterly intervals. For comparison we also show a later-vintage path in red.

In the top panel of Figure 8 we show the first ADS path, 12/5/2008. ADS shows a very deep recession, almost the deepest on record since 1960, bottoming out in 2008Q3, with movement toward recovery in late Q3 and early Q4, even if it had stalled a bit by early December. As it turned out, however, the Great Recession subsequently featured a growth rate “double dip”. The 12/5/2008 ADS path ends just after the first dip, which involved a sharp drop in September 2008 and an equally sharp rebound.¹¹ At the time it was easy to read the cards as saying that the recession was ending, and ADS was a bit too optimistic, moving upward toward recovery.

Now consider the remaining panels of Figure 8. In the second panel we show the next, and contrasting, 3/6/2009 ADS path. In the interim ADS has quickly learned the situation, the double dip in particular, and is very much on track, capturing the second dip in January 2009. ADS continues to climb steadily through the third and fourth panels (6/5/2009 and 9/3/3009, respectively), and by the time of the bottom panel (12/4/2009) it is clear that the Great Recession ended in June or July, with ADS basically fluctuating around 0 after that. (Recall that ADS=0 means average growth, not zero growth.)

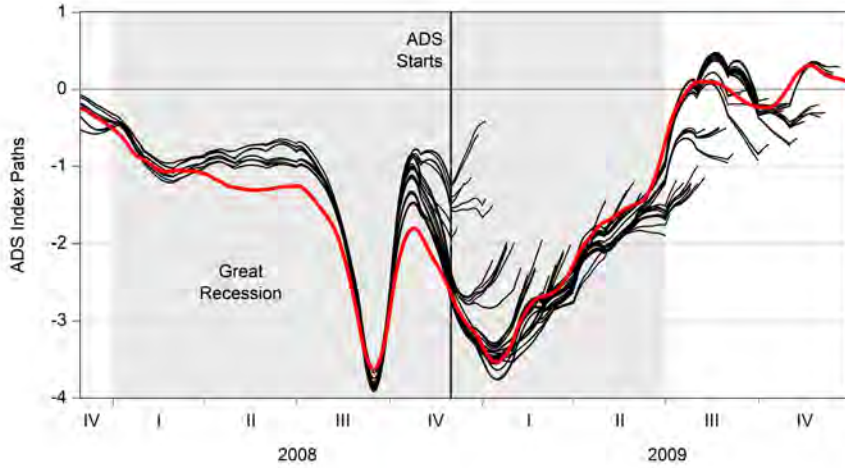
All told, the five quarterly real-time ADS paths generally match the ex post path closely, and they correctly identify the recession's end, well before the end of 2009 and indeed roughly 1.5 *years* before the official NBER announcement in September 2010.

To emphasize ADS timeliness, we plot the later-vintage ADS in Figure 8 all the way through 2010, which allows inclusion of the NBER's end-of-recession announcement on 9/20/2010, long after the fact and not helpful for real-time decision making.¹² ADS fills the gap left by the late-arriving NBER chronology, and it also provides a numerical measure that allows one to track the recession's pattern, depth, overall severity, etc., in addition to

¹¹In particular, according to the Federal Reserve's G.17 Industrial Production (IP) release of October 16, 2008, September IP was severely affected by a highly-unusual and largely exogenous “triple shock” (Hurricanes Gustav and Ike, and a strike at a major aircraft manufacturer), which caused an annualized September IP drop of nearly fifty percent. A similar pattern exists for Manufacturing and Trade Sales (MTS). IP and MTS also rebounded unusually sharply in October – indeed IP appears to “overshoot” – presumably in an attempt by manufacturers to make up for September's loss.

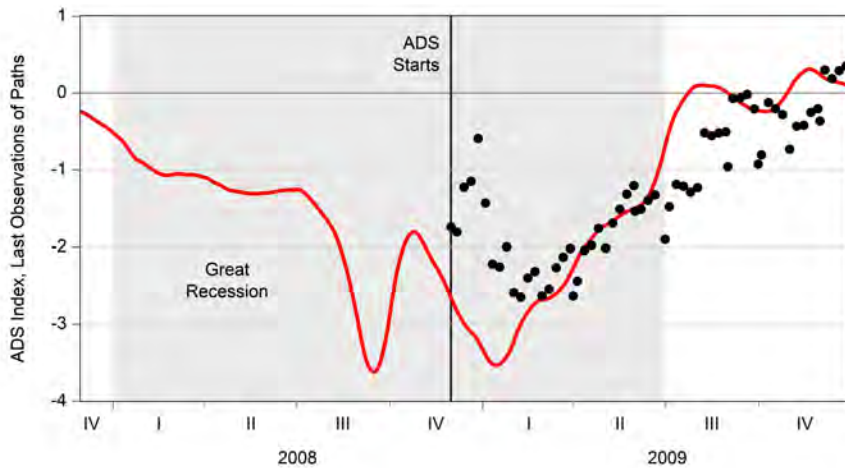
¹²Of course the NBER is not *seeking* to be helpful for real-time decision making; rather, they seek to meticulously construct the U.S. business cycle chronology of record, quite reasonably using all relevant information – even very late-arriving information.

Figure 9: Exiting the Great Recession: Real-Time ADS Path Plot



Notes: We show all 2008-2009 ADS paths since the first on 12/5/2008. We show real-time ADS paths in black, and a comparison late-vintage ADS path (December 2010) in red.

Figure 10: Exiting the Great Recession: Real-Time ADS Dot Plot



Notes: We show the last values of each 2008-2009 ADS path in black, with a comparison later-vintage ADS path (December 2010) superimposed in red.

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duration. For example and as recorded in Table 1, ADS identifies the Great Recession as the worst since 1960 and through 2010, with longest duration and second-greatest depth, resulting in the greatest overall severity (duration times depth).

In Figure 9 we show the complete path plot. Of course there are errors positive and negative as the recession evolves, but overall ADS performs well, sending a reliable and valuable signal for navigating the path out of recession. We show the corresponding dot plot in Figure 10.

5 Conclusion

We explored how views formed using a leading nowcast (ADS) evolved when entering the U.S. Pandemic Recession, which arrived abruptly and was caused by non-economic factors, tracking the evolution of real-time vintage beliefs and comparing them to a later-vintage chronology. ADS real activity growth plunged wildly in March 2020 and swung in real time as its underlying components swung, but it clearly returned to brisk growth by mid May, making the Pandemic Recession surely the deepest and likely the shortest on record.¹³ We also documented a strong negative relationship between the real-time ADS Pandemic Recession entry path and the concurrent real-time COVID-19 entry path, and we compared the ADS Pandemic Recession entry path to the earlier Great Recession exit path.

¹³The NBER has not yet announced the ending date of the Pandemic Recession.

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