

Theoretical Inflation for Unavailable Products

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Abstract Theoretical inflation diverges from official price statistics when products are unavailable due to stay-in-place behavior or due to stockouts caused by supply chain disruptions. In this paper, the word “theoretical inflation” designates inflation that is consistent with price measurement theory (Diewert and Fox 2020) (Diewert et al. 2019). It does not imply computational mistakes or data problems with official price statistics. This paper uses price measurement theory to develop a simple formula to calculate theoretical inflation. The paper then calibrates that simple formula to pre-pandemic research studying online shopping (Dolfen et al. 2021), tourist behavior (Glaeser, Kolko, and Saiz 2001), and stockouts (Corsten and Gruen 2004). Finally, the paper applies the simple formula to empirical data on product unavailability and calculates theoretical inflation by state and month from March 2020 until December 2021.

The paper finds large differences between official inflation and theoretical inflation. The official price level increased 1 percent in 2020 and then another 6 percent during 2021. In contrast, the theoretical price level associated with stay-in-place behavior increased 3 percent in 2020 and then decreased 1 percent in 2021 due to a partial return to normal. In addition, the theoretical price level associated with stockouts was minimal in 2020 and then increased 1 percent in 2021 due to supply chain disruptions. In total, the official inflation acceleration of 0.38 percentage point per month in 2021 diminishes to a theoretical inflation acceleration of only 0.15 percentage point per month. The paper also finds that theoretical inflation is higher in states with higher nominal consumption per capita. Hence, a measure of inequality which tracks the relative standard deviation of state income falls by 3 percent when state income is deflated by theoretical inflation.

Keywords Inflation, Price Index, Cost of Living Index, Regional Price Parity, Inequality, Coronavirus, COVID-19, Stay-in-Place, Supply Chain, Stockout, Lockdown, Social Distancing, New Goods

JEL codes E31, I18, K32

Introduction

Measured inflation rose sharply in 2021 according to statistics published by the U.S. Bureau of Economic Analysis (BEA 2022). Furthermore, a measure of inequality which tracks the relative standard deviation of real state income (BEA 2021) increased during the coronavirus pandemic. Both the recent inflation acceleration and the longer-term inequality increase have attracted public attention (Vinopal 2021) (Pew Research Center 2021) and have been discussed by policymakers at the Federal Reserve (Powell 2021) and in Congress (Manchin 2021). However, neither measured inflation nor measured inequality is theoretically consistent when products are unavailable due to either stay-in-place behavior or due to supply chain disruptions. In this paper, the word “theoretical” designates a cost-of-living index that is consistent with price measurement theory’s recommended treatment of unavailable products. It does not imply any data problems or computational mistakes with the price indexes published the U.S. Bureau of Labor Statistics (BLS), BEA, or other government agencies.

This paper updates and revises a previous BEA working paper (Soloveichik 2020). The new paper has four important changes. First, it broadens the scope of research to include stockouts due to supply chain disruptions. Second, it revises the theoretical inflation formula to recognize different theoretical inflation rates for nonessential products that are completely unavailable, nonessential products that are unavailable in-person but available remotely, essential products that are temporarily unavailable due to stockouts, and nonessential products that are temporarily unavailable due to stockouts. Third, it uses pre-pandemic survey data from the 2017 Economic Census and BEA’s 2019 state consumption statistics to calculate theoretical inflation separately for each state. Fourth, it extends the time series studied through December of 2021.

During 2020, the officially reported inflation rate of 0.09 percentage point per month increases to a theoretical inflation rate of 0.29 percentage point per month. During 2021, the officially reported inflation rate of 0.47 percentage point per month decreases to a theoretical inflation rate of 0.44 percentage point per month. In addition, a measure of inequality that tracks the relative standard deviation of real state income decreases 4 percent when state income is deflated by theoretical inflation due to stay-in-place behavior but increases 1 percent when state income is deflated by theoretical inflation due to product stockouts.

The paper is divided into six sections. Section 1 reviews the previous price measurement literature and adapts that literature to develop a simple formula to calculate theoretical prices when products are unavailable. Section 2 develops detailed estimates of consumer spending by category and state in 2019. Section 2 then shows that seemingly identical stay-in-place behavior or seemingly identical supply chain

disruptions impact states differently due to pre-existing differences in consumer spending patterns. Section 3 estimates actual stay-in-place behavior in each state from March 2020 until December 2021. Section 4 estimates actual stockout rates in each state from March 2020 until December 2021. Section 5 then calculates theoretical inflation for each state and month using the simple formula developed in section 1 and the data estimates in sections 2 to 4. Section 5 then discusses how theoretical inflation has evolved over time and across states. Finally, appendix A supplements section 1 with a model of tourist behavior that is used to calculate a theoretical price for completely unavailable products.

1. Brief Review of Price Measurement Literature

For simplicity, this paper focuses on calculating a Laspeyres price index for a basket of n products. Product prices in the base period ($t=0$) are designated as (p_{10}, \dots, p_{n0}) , spending weights for products in the base period are designated as (w_{10}, \dots, w_{n0}) , and product prices in the period t are designated (p_{1t}, \dots, p_{nt}) . If those vectors are known, then the Laspeyres formula is simple:

$$(1) \quad \text{Laspeyres Index}_t = w_{10}(p_{1t}/p_{10}) + w_{20}(p_{2t}/p_{20}) + \dots + w_{n0}(p_{nt}/p_{n0}).$$

The Laspeyres formula above cannot be calculated when prices are unobservable. This paper studies a scenario in which all products are available at the base period, but only products 1 to j are available in time t . The paper assumes that prices for unavailable products are unobservable, so analysts who desire to calculate a Laspeyres index must impute prices for products $j+1$ to n in time t . The paper designates the observable prices for available products as (p_{1t}, \dots, p_{jt}) and the imputed prices for unavailable products as $(ip_{j+1t}, \dots, ip_{nt})$. The Laspeyres formula is now:

$$(2) \quad \text{Theoretical Laspeyres Index}_t = w_{10}(p_{1t}/p_{10}) + \dots + w_{j0}(p_{jt}/p_{j0}) + w_{j+10}(ip_{j+1t}/p_{j+10}) + \dots + w_{n0}(ip_{nt}/p_{n0}).$$

BLS assumes that unobservable prices track observable prices for similar products (Gomes 2018). BLS's assumption appears to be quite accurate in normal economic times, and therefore its published price indexes normally track closely with price indexes that are consistent with price measurement theory (Bradley 2003). However, this paper argues that unobservable prices may not track observable prices during the coronavirus pandemic. As a result, price measurement theory is needed to impute unobservable prices and calculate inflation rates in 2020 and 2021.

Imputing Prices for Products That Are Completely Unavailable

There are no pre-pandemic papers studying theoretical prices for unavailable products during stay-in-place behavior. The reason for lack of previous literature is simple: public health authorities rarely—if ever—recommended broad stay-in-place behavior before the coronavirus pandemic. Instead, past stay-in-place recommendations were generally restricted to small high-risk groups, like travelers or individuals with known symptoms (Tognotti 2013). Because broad stay-in-place recommendations are so new, there is neither previous epidemiological research estimating its impact on disease transmission (Stone 2020) nor previous economic research estimating its impact on price indexes. Similarly, it is very rare for popular product categories to be completely unavailable for nonhealth reasons.

The **new goods literature** studies the theoretical price impact of introducing entirely new product categories to the market basket. The new goods literature typically uses economic theory and empirical data to create sophisticated demand models. The literature then solves those sophisticated demand models to impute prices for products before they are available (Hausman 1999) (Hausman 1997) (Petrin 2002) (Goolsbee and Petrin 2004) (Berndt et al. 1996) (Nordhaus 1996) (Diewert and Feenstra 2019) (Diewert et al. 2019). By construction, the Laspeyres price increase associated with a product disappearance is the exact converse of the Paasche price decrease associated with a product appearance. Hence, the theoretical background developed in those papers may shed light on the general problem of unavailable products. However, the sophisticated demand models used in those papers are difficult to create or solve when many broad product categories are suddenly unavailable.

This paper uses tourist behavior to impute prices for completely unavailable products. Based on the fact that tourists visit both rural and urban regions, the paper concludes that the theoretical cost of a vacation must be identical in both regions. There is rich economic literature showing that urban regions have higher prices than rural regions for seemingly similar housing units (Aten and D'Souza 2008) (Gyourko, Mayer, and Sinai 2013) (Glaeser and Gyourko 2018), physically identical goods (Stroebel and Vavra 2019), and physically identical nonhousing services (Paredes and Loveridge 2014). There is also a rich economic literature showing that urban regions have nonessential products like fine dining, live entertainment, or fashionable clothing stores that are unavailable in rural regions (Glaeser, Kolko, and Saiz 2001) (Florida 2018) (Couture et al. 2020). Hence, the imputed price for unavailable products in the rural region must be high enough to offset for the lower price of available products. Appendix A of the paper rigorously applies this intuition to empirical data and calculates that that theoretical inflation is 59 percent for completely unavailable products. Section 2 of the paper estimates that approximately 16 percent of aggregate consumer spending is completely unavailable during full stay-in-place behavior. Therefore, complete product unavailability contributes 9.4 percent (59 percent * 16 percent) to theoretical inflation during full stay-in-place behavior.

Imputing Prices for Products That Are Unavailable In-Person but Available Remotely

This section defines remote products as goods or services that can be purchased and delivered while socially distanced. Remote products can be purchased online, over the phone, by mail, at an outside pickup location, or at a vending machine. Goods purchased online are the most obvious example of remote products—but many services can be delivered remotely as well. For example, restaurants often provide food via take-out windows or delivery (Fantozzi 2021) and many doctors have started providing medical advice through video or telephone consultations (Patel et al. 2021). This paper uses product line detail from the 2017 Economic Census, academic research, and expert judgment to identify products that are unavailable in-person but available remotely during full stay-in-place behavior.

BLS's normal price measurement methodology calculates inflation by comparing prices for a particular product at a particular outlet over time. This methodology cannot calculate inflation when an in-person outlet closes and is replaced by an unaffiliated remote outlet because the closed in-person outlet has no current prices to link with past prices, and the remote outlet has no past prices to link with current prices (BLS 2018). On the other hand, this methodology does produce an inflation estimate when an in-person outlet switches to remote sales only. In that case, current remote prices are linked with past in-person prices without any adjustment for the changing sales channel. Furthermore, even outlets that are open in-person may have current remote prices linked to past in-person prices (BLS 2021).

The **outlet substitution bias literature** assumes that consumers are indifferent between the various outlets that sell a particular product (Reinsdorf 1993) (Hausman and Liebtag 2009) (Greenlees and McClelland 2008). In other words, the elasticity of substitution between outlets is assumed to be extremely high. If that same simplifying assumption is applied during the coronavirus pandemic, then the theoretical price increase for goods that are unavailable in-person would be the difference between their current remote price and their past in-person price. However, the outlet substitution bias literature focuses on standardized products that are bought for off-premises usage, and its assumptions may not apply to other types of products. For example, an in-person restaurant meal is a very different experience than a takeout restaurant meal. Therefore, this paper will not use the price measurement formulas developed in the outlet substitution bias literature.

The **variety bias literature** studies the theoretical price impact of introducing slightly new products within a product category or new retail outlets selling the same product. The variety bias literature typically assumes a very specific utility function, and then solves that utility function to calculate variety-adjusted price indexes for the category studied (Feenstra 1994) (Broda and Weinstein 2010) (Handbury and Weinstein 2014). Pre-pandemic research studying Visa credit card users (Dolfen et al. 2021) estimated a substitution elasticity of 4.3 between online merchants and offline merchants. This substitution elasticity means that a forced switch from the desired purchasing method to the undesired purchasing method is theoretically equivalent to a 23 percent ($1/4.3$) price increase.¹ Section 2 of the paper estimates approximately 10 percent of aggregate consumer spending is unavailable in-person but available remotely during full stay-in-place behavior. Therefore, in-person unavailability during full stay-in-place behavior results in theoretical inflation of 2.3 percent (23 percent * 10 percent). This is over and above the 9.4 percent theoretical inflation due to complete product unavailability.

Imputing Prices During Product Stockouts

Product stockouts occur when a product is listed for sale but temporarily unavailable. One might think that product stockouts have a low welfare cost because shoppers can select a close substitute for the missing item (Gruen and Corsten 2007). In fact, shoppers plan their purchases before visiting the store (Su and Zhang 2009), so an unexpected stockout can have larger welfare costs than a product that is known to be unavailable. For example, a consumer might plan a dinner menu before discovering that some necessary ingredients are not available at the first grocery store visited. There is a large literature studying the impact of stockouts on store profits (Sanchez-Ruiz et al. 2018). However, the literature studying the impact of stockouts on consumers is much smaller and focused on the emotional impact (Fitzimmons 2000) or the qualitative impact of competition (Matsa 2011).

Theoretical inflation for essential product stockouts is calculated from the shopping literature. A consumer survey reveals that 31 percent of missing grocery items are so necessary that shoppers visit another store to find them (Corsten and Gruen 2004). Academic research estimates that the fixed cost of a store visit averages about five times the price of the item studied (Mohir and Sudhir 2021). Hence, the consumer welfare loss from a 10 percent stockout rate is at least 15 percent ($10 \text{ percent} * 0.31 * 5$). In other words, a consumer with a grocery shopping list of \$100 would pay a premium of \$15 to get all of the items at one store rather than make multiple trips.

¹ The paper also calculates a substitution elasticity of 6.1 between offline merchants. Therefore, the theoretical price increase may be slightly lower if the relevant substitution is to an essential store rather than online purchase.

Theoretical inflation for nonessential product stockouts is likely smaller than the theoretical inflation for essential product stockouts. Nonessential items are not necessary for life, and therefore missing items do not necessarily prompt an immediate trip to another store. In addition, most nonessential items have higher unit values than grocery items. Accordingly, the fixed cost of an additional store trip represents a smaller fraction of the nonessential item's list price. Previous research specifically tracking the welfare cost of nonessential product stockouts could not be located. For now, this paper will assume that consumers respond to nonessential product stockouts by purchasing the item remotely. Hence, theoretical inflation from a stockout is assumed to be the same 23 percent as theoretical inflation for products which are unavailable in-person but available remotely.

Price Measurement Questions Not Studied in This Paper

This paper does not study quality changes. Some economists have suggested viewing coronavirus-related product unavailability through the lens of quality change (Cowen 2020). In addition, emergency medical care quality decreases when hospitals are overcrowded (French et al. 2021) (Woodworth 2020). However, measuring quality changes consistently for all goods and services impacted by the coronavirus pandemic would be a difficult empirical project. Furthermore, some changes may be captured in the quality adjustments that are already part of BLS's published price indexes (BLS 2019).

This paper also does not study consumer utility. In some models, household inventories of previously purchased goods and home production can partially substitute for products that are currently unavailable in the market sector (Becker 1965). In other models, network effects mean that collective impact of product unavailability is not necessarily equal to individual impact of product unavailability (Liebowitz and Margolis 1994). Researchers who are focused on the dynamic problem of measuring consumer utility throughout the coronavirus pandemic may need to model both household inventories, home production, and network effects carefully.

2. Consumer Spending by State, Category, and Kind of Business

This section splits the 15 consumer spending categories tracked in BEA's state consumption statistics² into 56 subcategories that correspond better with coronavirus-related product unavailability. The 56 subcategories of consumer spending include health spending paid for by insurance, gambling services, and other spending categories that BLS treats as out-of-scope for the consumer market basket (BLS 2018). To start, state-level credit card transaction data from Earnest Research is used to split each goods category between in-person purchases and remote purchases. Next, consumer spending categories that contain a mix of essential and nonessential products are split between those two product types. Finally, consumer spending categories that contain some products that are particularly vulnerable to supply chain disruptions and other products that are less vulnerable are split between those two product types. These splits are based on state-level product detail from the 2017 Economic Census, academic sources, and expert judgment.

Calculating the Impact of Stay-in-Place Behavior by State

These 56 subcategories can be aggregated by their treatment under typical public health guidelines. Across the United States, average spending per person in 2019 was: \$6,936 for essential goods,³ \$3,173 for nonessential goods purchased remotely,⁴ \$3,397 for nonessential goods purchased in-person, \$7,862 for essential housing, \$5,082 for essential services, \$7,129 for nonessential remote services, and \$9,746 for nonessential in-person services. Stay-in-place behavior impacts the one-third of consumer spending which is both nonessential and in-person.

² <https://apps.bea.gov/itable/itable.cfm?ReqID=70&step=1>

³ This category includes alcohol, tobacco, pet food, automobile parts, and other products that are not necessary for human survival but are treated as necessary by the purchasers.

⁴ This includes vehicles purchased at dealerships because vehicle shopping is done outdoors.

Figure 1. Products That Are Completely Unavailable During Full Stay-in-Place Behavior

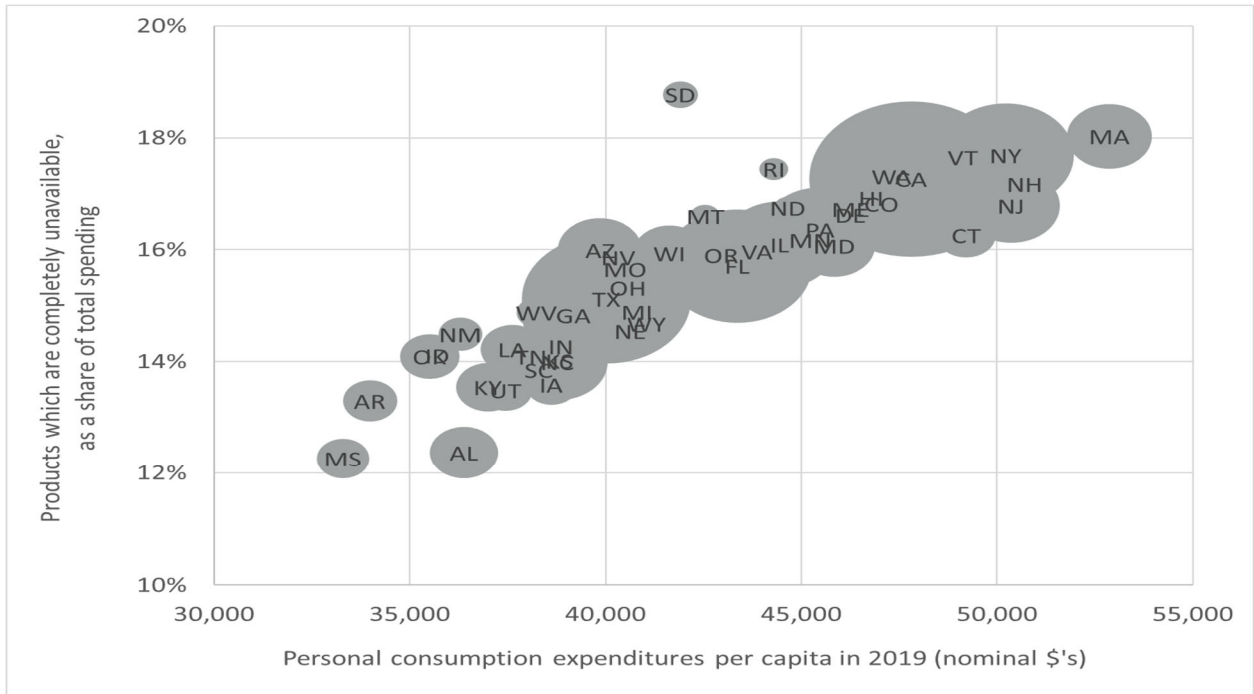
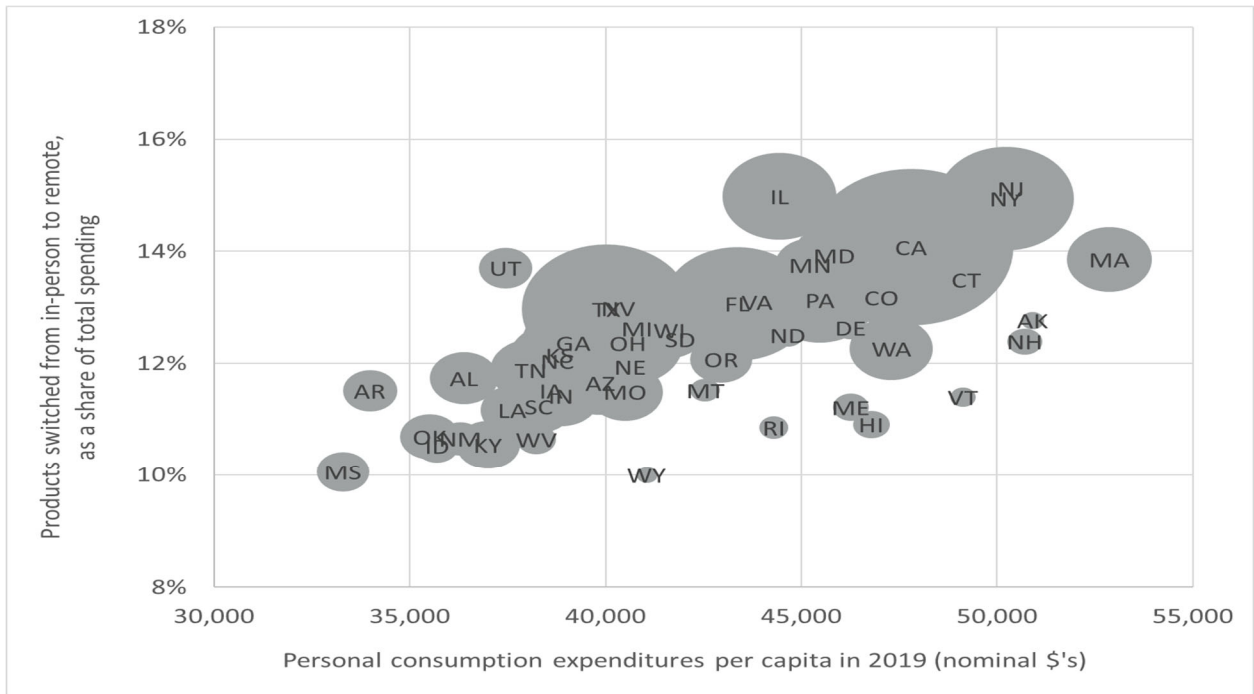


Figure 2. Products That Are Unavailable In-Person During Full Stay-in-Place Behavior



Figures 1 and 2 shows that stay-in-place behavior impacts a much larger share of spending in states with higher nominal consumption per capita. This positive correlation is primarily driven by the fact that essential products, which are exempted from stay-in-place guidelines, account for a much smaller share of spending in high income states. Low income states also buy a much larger share of nonessential products at essential retail businesses that remain open even during full stay-in-place behavior. Section 1 estimated that theoretical inflation equals: 59 percent of spending on nonessential products that are completely unavailable plus 23 percent of spending on nonessential products that are forced to switch from in-person to remote. Hence, it is clear that the same full stay-in-place behavior creates more theoretical inflation in states with high nominal consumption per capita.

Calculating the Impact of Stockouts by State

These 56 subcategories can also be aggregated by vulnerability to supply chain disruptions. Supply chain issues are often illustrated with pictures of goods missing from retail shelves (Elwood 2022), but cable sports can have a stockout when a game is canceled due to coronavirus (Sherman 2020) and restaurants can have a stockout when critical ingredients are not delivered (Dominko 2021). Even before the coronavirus pandemic, stockouts for individual products were common due to supply shocks or unexpectedly high demand (Andersen 1996). However, the total number of stockouts has recently increased significantly due to supply chain disruptions and other economic changes (Gamio and Goodman 2021). The theoretical inflation numbers calculated in this paper study the impact of coronavirus-related increases to the stockout rate rather than the total impact of all stockouts.⁵

Data tracking specific product vulnerability to coronavirus-related supply chain disruptions could not be located. For now, the paper uses stockout rates for goods from previous academic research (Bils 2016) (Matsa 2011) and expert judgment to calculate relative stockout rates for products vulnerable to supply chain disruptions. The paper then benchmarks the relative stockout rates to an absolute stockout rate reported by IRI for consumer-packaged edibles in February 2020.⁶ The paper calculates that a supply chain shock that doubles the normal stockout rate would result in \$605 of essential goods unavailable, \$1,067 of nonessential goods unavailable, and \$324 of services unavailable.

⁵ Gasoline shortages due to the Colonial pipeline hack are assumed to be non-coronavirus related and excluded.

⁶ For a variety of technical sampling issues, those two papers report lower stockout levels than consumers likely experience (Matsa 2011). Therefore, their numbers cannot be used without adjustment.

Figure 3. Essential Products Stockout from a Doubling in the Normal Stockout Rate

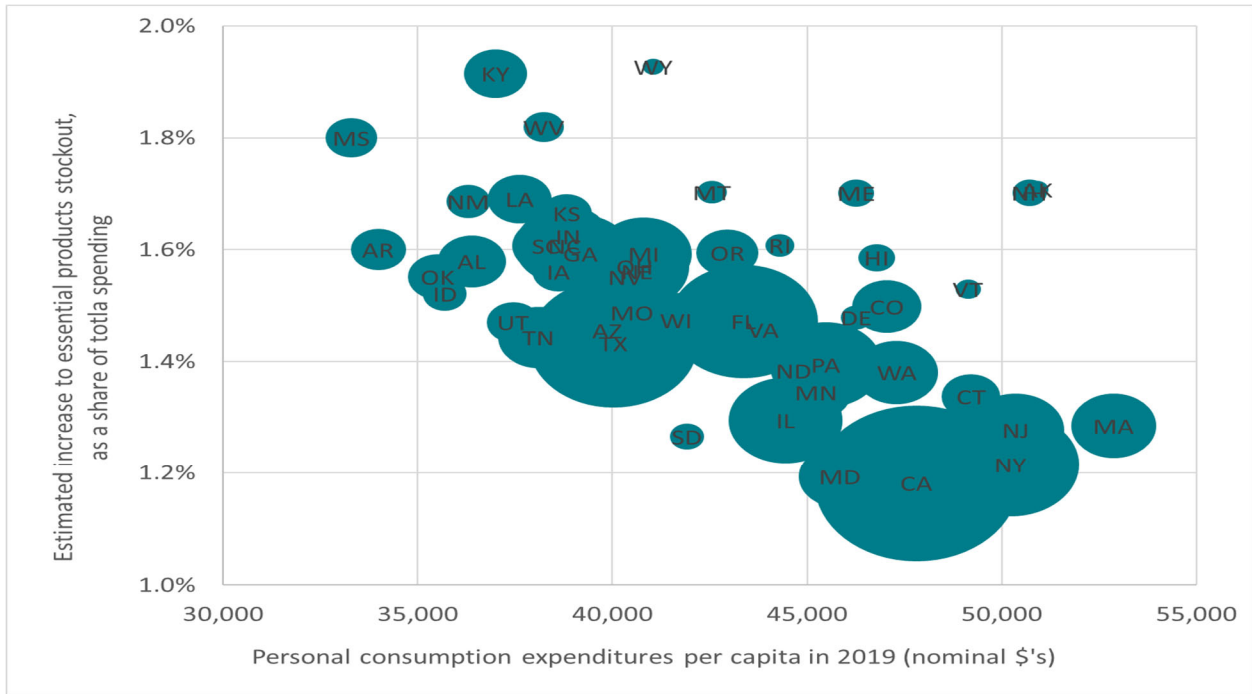
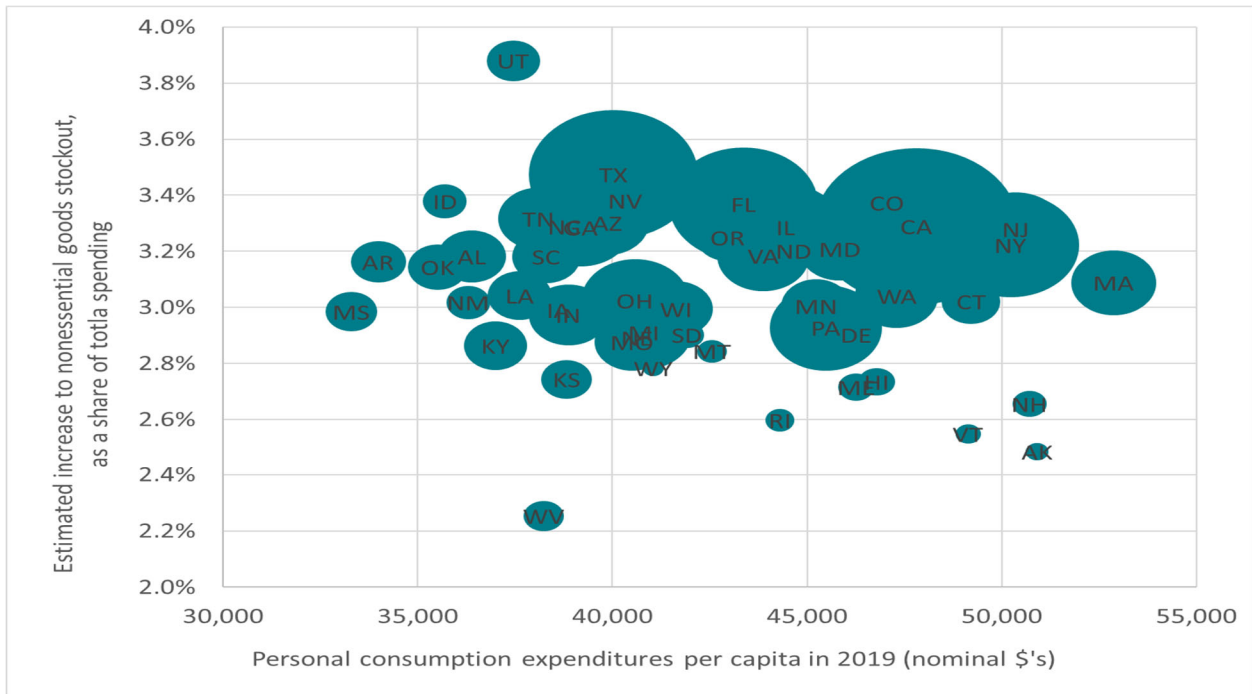


Figure 4. Nonessential Products Stockout from a Doubling in the Normal Stockout Rate



Figures 3 and 4 show that the stockout share of spending is negatively correlated with nominal consumption per capita. As a result, nationwide supply chain disruptions create more theoretical inflation in states with lower nominal consumption per capita. In contrast, figures 1 and 2 showed that full stay-in-place behavior creates more theoretical inflation in states with higher nominal consumption per capita. The net correlation between total theoretical inflation and state income is inherently ambiguous and depends on which coronavirus-related shock is stronger in a particular month.

3. Actual Stay-in-Place Behavior by State

This section studies actual stay-in-place behavior. A large portion of the stay-in-place behavior is due to explicit stay-in-place rules issued by city or state governments (Dave et al. 2020; Allcott et al. 2020). However, many businesses closed voluntarily and many consumers avoided open businesses voluntarily (Takashi 2020) (Molla 2020). Conversely, some businesses started reopening before government stay-in-place orders were lifted (Lee 2020). This paper does not attempt to separately estimate the contribution of explicit rules, business decisions, and consumer decisions; rather, it studies how all three factors combine to create actual stay-in-place behavior.

The paper estimates stay-in-place behavior indirectly with the help of several strong assumptions. First, and most important, the paper assumes that stay-in-place behavior does not impact time spent at essential businesses. Second, the paper assumes that adjusted time spent at retail and recreational locations proxies for both stay-in-place behavior regarding those locations⁷ and stay-in-place behavior regarding other nonessential locations. Finally, the paper assumes that theoretical inflation due to stay-in-place behavior varies linearly with adjusted time spent at “retail and recreational locations.” For example, a month where adjusted time spent at retail and recreational locations dropped 20 percent is assumed to have double the theoretical inflation as a month where adjusted time dropped 10 percent. The precise level of theoretical inflation is very sensitive to changing these three assumptions, but the qualitative results over time or across states are more robust.

⁷ From Google’s published COVID-19 Community Mobility Reports <https://www.google.com/covid19/mobility>. Documentation available at https://www.google.com/covid19/mobility/data_documentation.html?hl=en reveals that “retail and recreation” category includes libraries, museums, and other government locations. The empirical analysis in this paper adjusts for those locations, but results are substantially similar without adjustment.

Calculating Actual Stay-in-Place Behavior

It might seem simple to measure stay-in-place behavior. After all, Google publishes mobility estimates that track time spent at retail and recreational locations by day and county. These data are published online and are extensively documented by Google. Summary statistics for selected regions are shown below.

Figure 5. Unadjusted Stay-in-Place Behavior for Selected States by Month

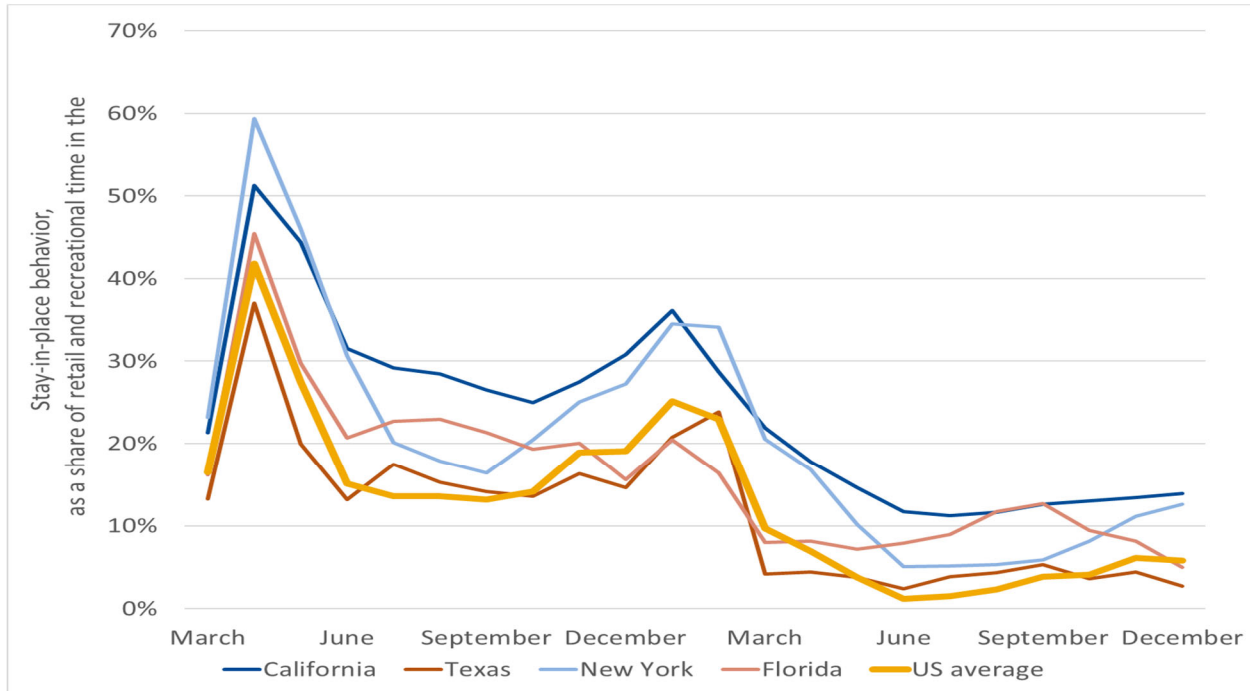


Figure 5 clearly matches the qualitative pattern of the coronavirus pandemic. Stay-in-place behavior spiked quickly early on and then partially recovered to hover at around 20 percent of the maximum possible for the next year. After vaccines were introduced in the spring of 2021, stay-in-place behavior started dropping further and was quite low in December 2021. The mobility changes reported by Google are much larger than any previous mobility variation reported in the American Time Use Survey.

However, Google's published data are a biased measure of stay-in-place behavior. Previous research has shown that retail and recreation time is higher during pleasant weather (Soloveichik 2020) and higher when sunset is later (Farrell et al. 2016). Google's published data are all reported relative to a base period of January 3 to February 6 of 2020. Northern states typically have unpleasantly cold weather and very early sunsets during that base period. In contrast, southern states have more moderate weather and slightly later sunsets during the base period. Accordingly, Google's published data are reported relative to a lower baseline for northern states and is therefore biased towards showing less compliance with public health guidelines in those states.

Google's published data are also biased across states for a more subtle reason. The Google category "retail and recreation" includes essential businesses like auto part stores and general merchandise stores. As a result, even full stay-in-place behavior would not reduce time spent at retail and recreational locations to zero. Furthermore, states with lower nominal consumption per capita tend to have more general merchandise stores and fewer nonessential businesses. Hence, those states will appear to have less stay-in-place behavior even if actual behavior is identical across states.

Finally, Google's published data are biased over time due to the seasonal factors. Weather is the most important seasonal factor. The paper first estimates the impact of weather using daily temperature data by county from DegreeDays.net⁸ and daily sunset time calculated from county longitude and latitude. The paper then adjusts Google's reported mobility statistics for both seasonal and idiosyncratic variations in weather over time. Holidays are another important seasonal factor. The paper estimates the normal impact of using historical data from the American Time Use Survey and then adjusts Google's reported mobility statistics for that normal impact. In addition, the paper also adjusts Google's mobility statistics for apparent changes in the number of cellphones tracked in that county/day observation.⁹ Finally, the paper weights Google's **relative** mobility numbers by normal retail and recreational time in each county to get aggregate retail and recreational time by day and state.¹⁰

⁸ The paper's regression summarizes weather into three statistics: weighted time below 70° F, weighted time above 70° F, and daily temperature variation. The paper interacts all three weather statistics with sunset time. Weather data was not purchased for August to December 2021, and so the paper uses weather on the same date in 2020 as a proxy. By design, this proxy captures broad seasonal effects rather than short-term variation.

⁹ The paper sums four broad Google time usage categories ("retail and recreational locations," "grocery and pharmacy locations," "workplaces," and "residential locations") to get total time. Changes in the total time relative to the winter base period are assumed to be due to changes in population or cellphone usage per person.

¹⁰ County population is the main factor determining a county's daily weight. But the paper also adjusts for differences in retail and recreational time per person across metropolitan statistical areas and days of the week.

Figure 6. Adjusted Stay-in-Place Behavior for Selected States by Month

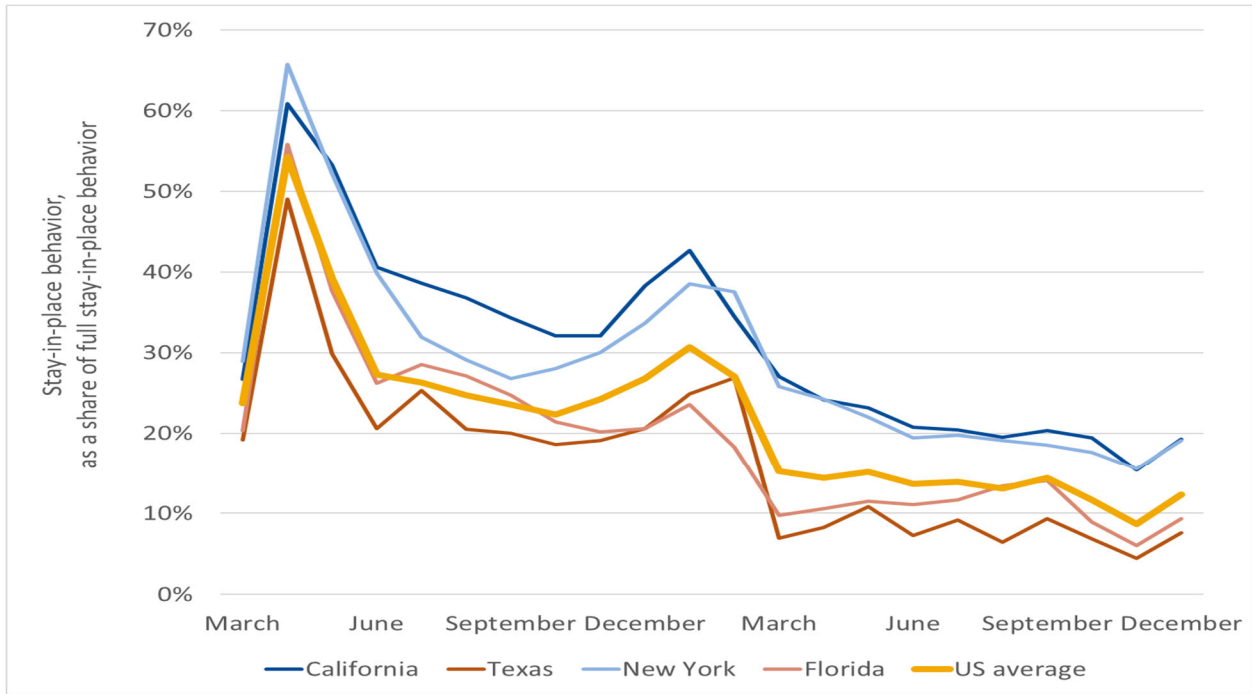


Figure 7. Adjusted Stay-in-Place Behavior by State, Mean from 3/20 to 12/21

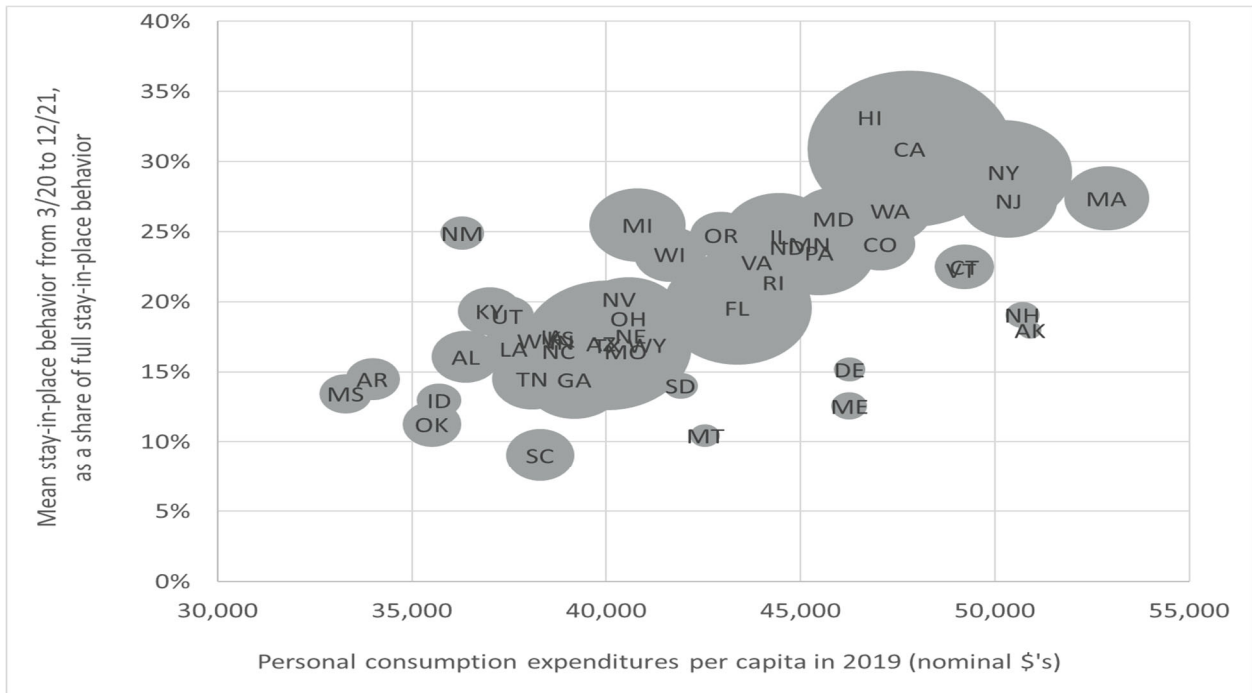


Figure 6 shows that seasonal adjustments have an important impact on stay-in-place behavior. Most noticeably, adjusted stay-in-place behavior falls slower than unadjusted stay-in-place behavior during spring 2020 and spring 2021. In other words, some of the increase in mobility shown by Google's published statistics is due to normal seasonal variation associated with more pleasant outdoor conditions and holidays.¹¹ Furthermore, the differences in adjusted stay-in-place behavior across states are larger and more stable than the differences in unadjusted stay-in-place behavior.

Figure 7 shows a strong positive correlation between nominal consumption per capita and stay-in-place behavior during the coronavirus pandemic. It seems plausible that adherence to public health advice is a normal good and states with higher nominal consumption per capita can afford more adherence than other states. This paper focuses on measuring consumer prices and will not examine any health consequences associated with different levels of adherence.

4. Actual Stockout Rates by State

The term "supply chain disruption" is used to describe many types of shocks. For example, a local coronavirus pandemic might force a factory to shut down temporarily. Or transportation problems might prevent an existing product from being delivered to stores. Or a store might receive a product delivery but be too short-staffed to sell it to end users. Or a good's price might be set so low that it sells out completely before the next shipment arrives. This paper will estimate the total impact of supply chain disruptions on stockout rates without decomposing that total by product or type of shock.

Calculating Stockout Rates by State and Over Time

IRI supplies stockout data for edible consumer packaged goods. Unlike Google, IRI only publishes recent data online and the historical data must be purchased. Detailed documentation for the IRI supply index could not be located, but one early pamphlet suggests that IRI uses observed sales transactions to estimate stockout rates. In addition, verbal discussion with an IRI sales representative revealed that IRI's data are taken from large grocery store chains and other businesses that sell large quantities of food. To focus on the coronavirus impact, the paper adjusts IRI's data for seasonal patterns in the food stockout rate noted in previous research (Bils 2016).

¹¹ Monday holidays like Memorial Day are typically associated with more retail and recreational time. In addition, the decrease in shopping time on Thanksgiving and Christmas themselves is more than outweighed by an increased mobility for each day of the week during the base period. So, a single isolated holiday like Martin Luther King Jr. Day has little impact on the base mobility level.

Figure 8. Relative Stockout Rate for Selected States by Month

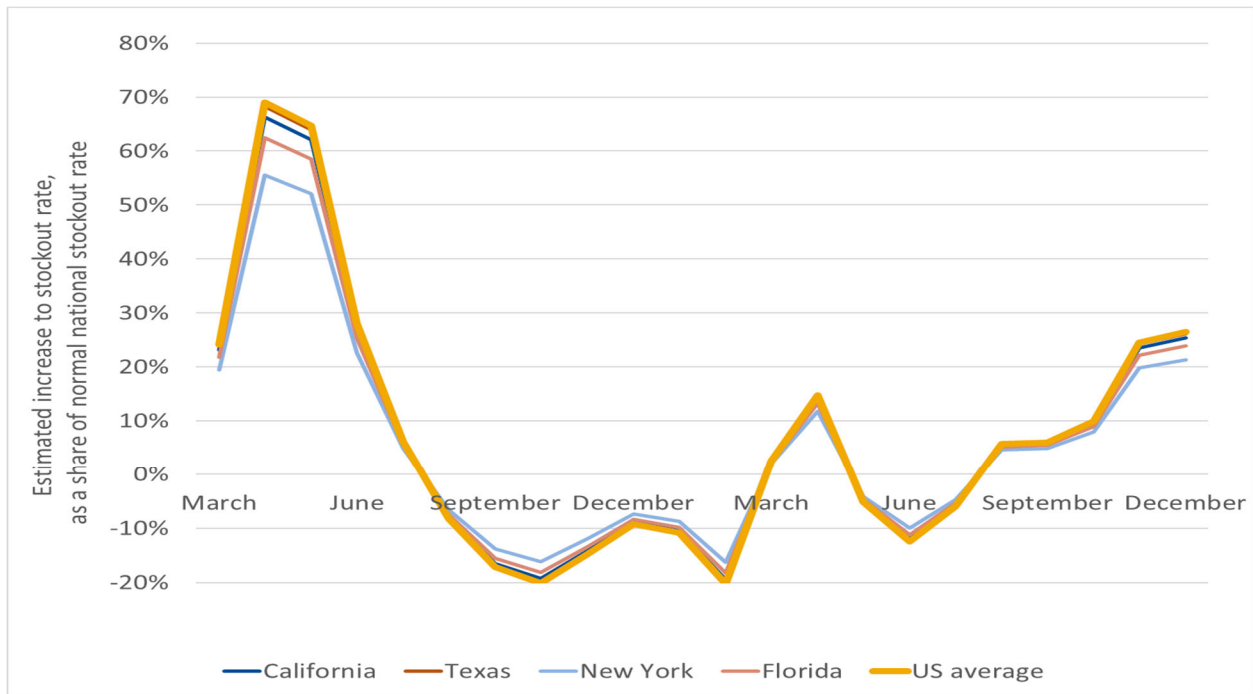


Figure 8 shows that the stockout rate rose quickly in the spring of 2020 and then returned to normal for almost a year. The stockout rate then started rising again in the second half of 2021 and is now noticeably above normal. Figure 8 also shows that supply chain disruptions were similar across states.¹²

Just like with stay-in-place behavior, the paper makes several strong assumptions to measure overall stockout rates. First, the paper assumes that spending patterns in 2019 predict potential spending for each product category impacted by stockouts. Second, the paper assumes that the stockout rate for edible consumer packaged goods proxies for the overall stockout rate. Consistent with that assumption, academic research shows that nonessential good stockouts experienced the same general pattern as essential good stockouts during the first year of the coronavirus pandemic (Cavallo and Kryvtsov 2021). Third, the paper assumes that all products studied have a stockout rate well below 100 percent. Thanks to that assumption, the paper does not need to consider nonlinear effects of product stockouts around 100 percent. The estimated welfare cost of stockouts is sensitive to changing these three assumptions, but the qualitative results over time or across states are more robust.

¹² Full historical data from IRI was not purchased for this paper draft. Instead, the paper imputes monthly stockout rates in each state based on sample data tracking New York state's weekly stockout rates and public data from the weeks in which IRI's data could be located online. The public data showed a very high correlation between weekly stockout rates across states. Hence, the paper is able to impute stockout rates in each state using New York data.

5. Theoretical Inflation Over Time and Across States

This section calculates theoretical inflation for each state and month. For stay-in-place behavior, the paper first applies the simple formula developed in section 1 to the data in figures 1 and 2 to calculate theoretical inflation for each state during full stay-in-place behavior. The paper then multiplies that inflation during full stay-in-place behavior with the relative stay-in-place behavior shown in figures 6 and 7 to calculate theoretical inflation for each state during actual stay-in-place behavior. For supply chain disruptions, the paper first applies the simple formula developed in section 1 to the data in figures 3 and 4 to calculate theoretical inflation for each state during a hypothetical shock that doubles normal stockout rates. The paper then multiplies that inflation with the relative increase to stockout rates shown in figure 8 to calculate theoretical inflation for each state due to supply chain disruptions.

Figure 9. Theoretical Inflation Due to Product Unavailability for Selected States by Month

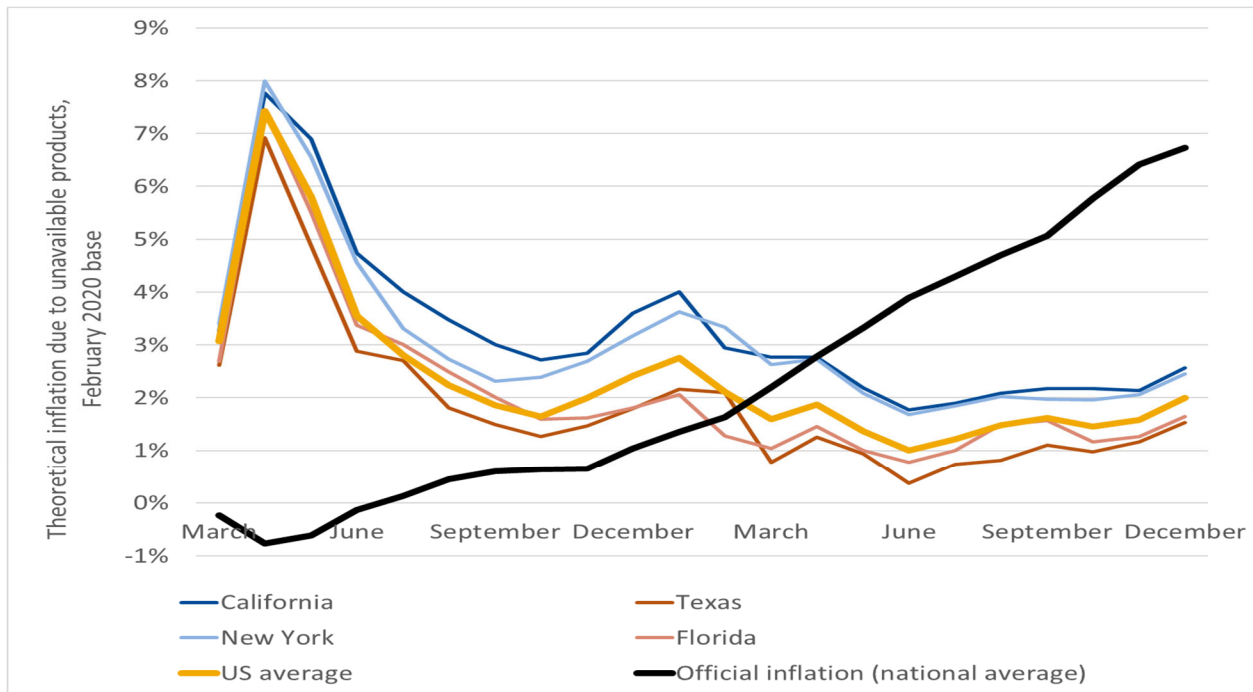


Figure 10. Average Theoretical Inflation by State, 3/20-9/21

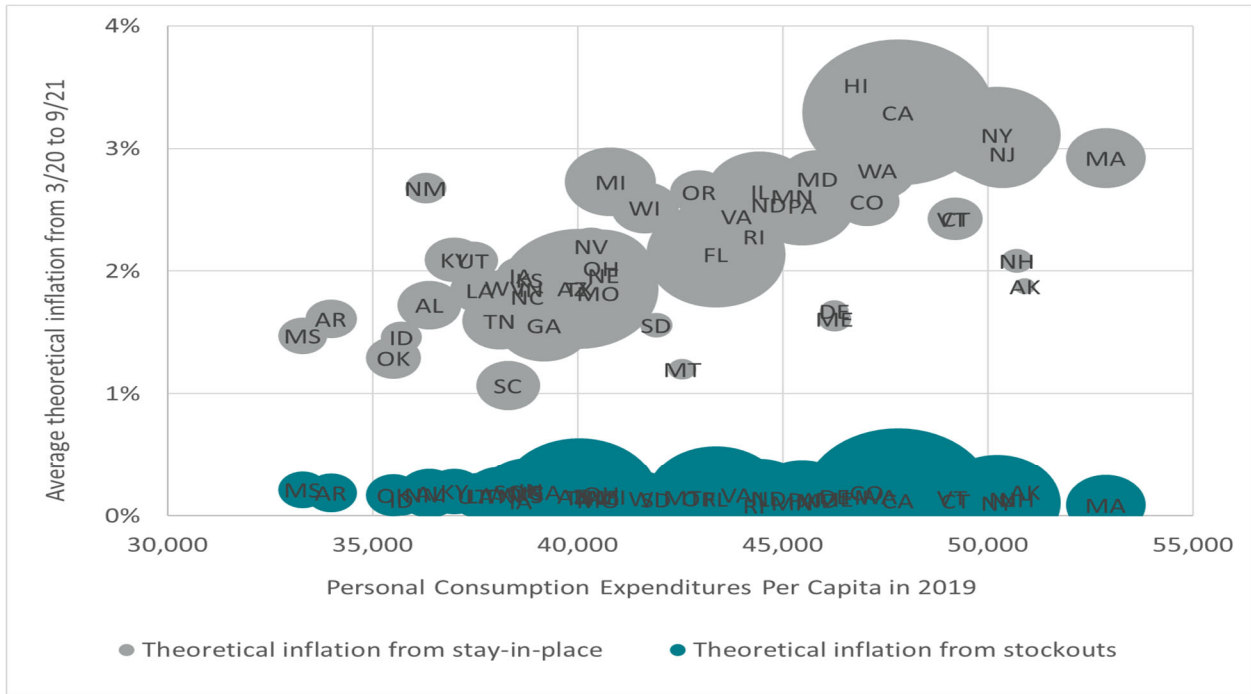


Figure 11. Average Theoretical Inflation by State, 10/21-12/21

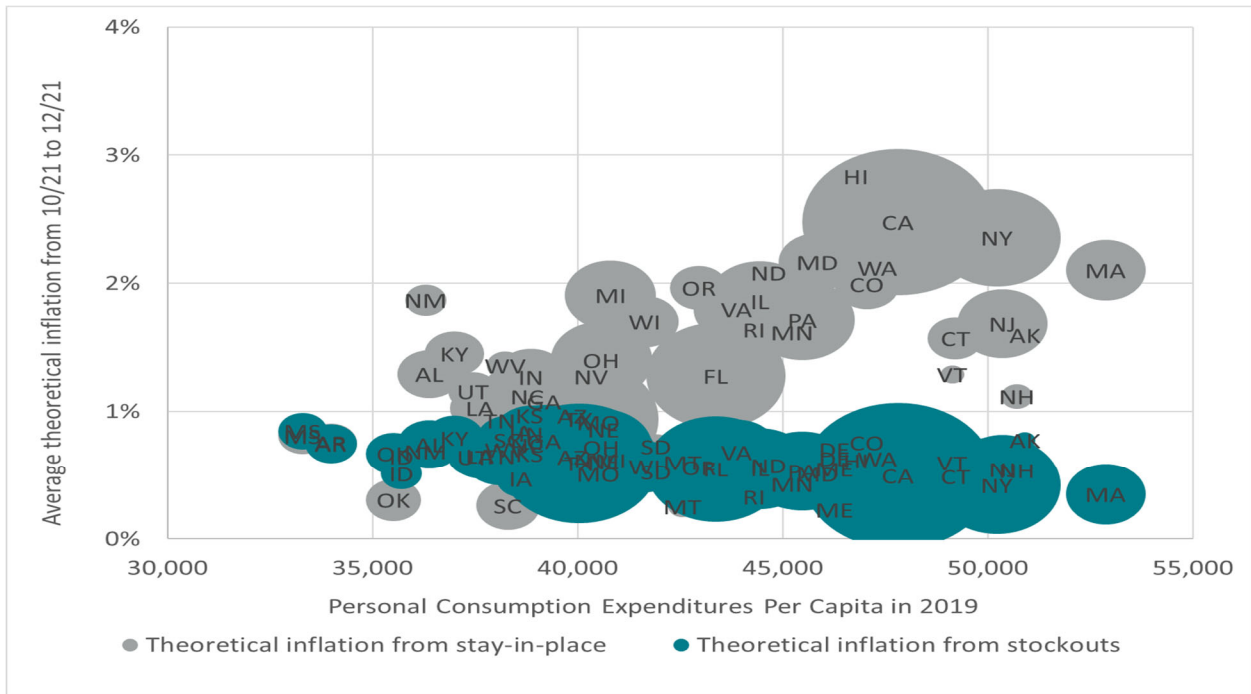


Figure 9 shows that theoretical inflation in selected months is comparable in size to the official inflation rate. Over the past year, many journalists and policymakers have extensively discussed the welfare costs associated with the official inflation shown in the black line (Adamczyk 2021) (Walsh 2021) (Powell 2021) (Manchin 2021). This paper argues that the welfare costs associated with theoretical inflation may also be important and should be studied as well.

Figures 10 and 11 show that stay-in-place behavior accounted for the lion's share of theoretical inflation early in the pandemic and still accounts for the majority of theoretical inflation in most states. But stockouts have increased in recent months and now account for a majority of theoretical inflation in some states. This shift in relative importance may explain why the supply chain crisis is getting so much more attention now than it did early in the coronavirus pandemic (Gamio and Goodman 2021).

Figures 10 and 11 also show that states with more nominal consumption per capita have consistently higher theoretical inflation due to stay-in-place behavior. Those same states also have slightly lower theoretical inflation due to product stockouts. For the period March 2020 until September 2021, average theoretical inflation due to stay-in-place behavior has been much higher than theoretical inflation due to product stockouts. As a result, that period had a strong positive correlation between state consumption per capita and theoretical inflation. For the period October 2021 until December 2021, average theoretical inflation due to stay-in-place behavior has been similar in magnitude to average theoretical inflation due to product stockouts. As a result, that period had a much weaker correlation between state consumption per capita and theoretical inflation.

Figure 12. Relative Standard Deviation of Income Across States Over Time



Figure 12 shows that the relative standard deviation of real state income is noticeably more equal when income is deflated with the theoretical inflation associated with stay-in-place behavior. In contrast, deflating income by the theoretical inflation associated with product stockouts increases the relative standard deviation of income across states during quarters with supply chain disruptions.

Conclusion

This paper measures theoretical inflation when products are unavailable due to stay-in-place behavior or stockouts. The paper finds large differences between official inflation trends and theoretical inflation trends. Official inflation rates show that the price level increased 1 percent in 2020 and then 6 percent in 2021. In contrast, the theoretical price level associated with stay-in-place behavior increased 3 percent in 2020 and then decreased 1 percent in 2021 as behavior started returning to normal. In addition, the theoretical price level associated with stockouts was minimal in 2020 and then increased 1 percent in 2021 due to supply chain disruptions. In total, the official inflation acceleration of 0.38 percentage point per month in 2021 diminishes to a theoretical inflation acceleration of only 0.15 percentage point per month. The paper also finds that a measure of inequality that tracks the relative standard deviation in real state income falls by 3 percent when state income during the coronavirus pandemic is deflated by theoretical inflation.

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Appendix A. Regional Model to Calculate Theoretical Prices for a Completely Unavailable Product

The paper's model assumes that rational tourists choose a destination that maximizes utility for a given vacation budget. Tourists are generally not affected by nonprice regional factors like jobs, schools, or income taxes. Furthermore, nearby urban and rural regions typically have similar weather and travel costs. As a result, the presence of tourists in the urban region strongly suggests that tourists derive sufficient utility from amenities that are only available in urban regions to outweigh the higher urban prices (Carlino and Saiz 2019).

General Model Setup

This paper begins by setting up a general model of regional price differences in an economy with four products: one hotel product (h), one broadly available good (g), one broadly available nonhotel service (s), and one amenity (a). Next, the model assumes that there are two regions, one rural (R) and one urban (U), which each have their own prices. In order to reduce the number of coefficients, normal urban prices for each of the four products is set at 1. The prices in region R are designated (p_{hR} , p_{gR} , p_{sR} , and p_{aR}). Finally, the paper assumes that there are two types of consumers in the economy, tourists (T) and locals (L). Tourists and locals pay the same price for a particular product in a particular region, but they allocate their budgets differently. The spending share for tourists is designated as (w_{hT} , w_{gT} , w_{sT} , and w_{aT}) and the spending share for locals is designated as (w_{hL} , w_{gL} , w_{sL} , and w_{aL}). By construction, the four spending shares for tourists sum to w_T and the four spending shares for locals w_L , with $w_T + w_L = 1$.

Formulas to Calculate Regional Price Differences

If all products are available in both regions and prices are observable, then it is straightforward to calculate average rural prices for each group:

- (1) Tourist Prices $= (w_{hT} * p_{hR} + w_{gT} * p_{gR} + w_{sT} * p_{sR} + w_{aT} * p_{aR}) / w_T$
- (2) Local Prices $= (w_{hL} * p_{hR} + w_{gL} * p_{gR} + w_{sL} * p_{sR} + w_{aL} * p_{aR}) / w_L$
- (3) Combined Prices $= (w_{hT} + w_{hL}) * p_{hR} + (w_{gT} + w_{gL}) * p_{gR} + (w_{sT} + w_{sL}) * p_{sR} + (w_{aT} + w_{aL}) * p_{aR}$

However, the price calculations are more complicated when the rural region does not offer the amenity product. As mentioned earlier, the formula for calculating price levels requires a price for every product in the market basket—so the analyst must impute rural prices for amenity products. This imputed price is designated ip_{aR} . Average rural prices for each group are:

$$(4) \quad \text{Tourist Prices} = (w_{hT} * p_{hR} + w_{gT} * p_{gR} + w_{sT} * p_{sR} + w_{aT} * ip_{aR}) / w_T$$

$$(5) \quad \text{Local Prices} = (w_{hL} * p_{hR} + w_{gL} * p_{gR} + w_{sL} * p_{sR} + w_{aL} * ip_{aR}) / w_L$$

$$(6) \quad \text{Combined Prices} = (w_{hT} + w_{hL}) * p_{hR} + (w_{gT} + w_{gL}) * p_{gR} + (w_{sT} + w_{sL}) * p_{sR} + (w_{aT} + w_{aL}) * ip_{aR}$$

BEA's general methodology uses prices for similar products as a proxy for the unavailable products. In this simplified model, available rural services are assumed to be a proxy for the unavailable rural amenity. Given that assumption, the average rural prices for each group are:

$$(7) \quad \text{Quasi-BEA Tourist Price} = (w_{hT} * p_{hR} + w_{gT} * p_{gR} + w_{sT} * p_{sR} + w_{aT} * p_{sR}) / w_T$$

$$(8) \quad \text{Quasi-BEA Local Price} = (w_{hL} * p_{hR} + w_{gL} * p_{gR} + w_{sL} * p_{sR} + \dots + w_{aL} * p_{sR}) / w_L$$

$$(9) \quad \text{Quasi-BEA Combined Prices} = (w_{hT} + w_{hL}) * p_{hR} + (w_{gT} + w_{gL}) * p_{gR} + (w_{sT} + w_{sL} + w_{aT} + w_{aL}) * p_{sR}$$

Calculating Theoretical Prices for Completely Unavailable Amenities

This paper uses an alternative methodology to calculate prices for the unavailable amenity. The alternative requires two additional assumptions: (1) tourists regularly visit both the rural and urban regions and (2) the rural region and the urban region have similar nonprice attributes for tourists (for example, weather and travel distance). If those two assumptions hold, then the tourist basket that can be purchased for a fixed vacation budget must be identical in both regions. In other words, theoretical prices in the rural region must be equal to prices in the urban region, which are set at 1:

$$(10) \quad 1 = \text{Theoretical Tourist Prices} = w_{hT} * p_{hR} + w_{gT} * p_{gR} + w_{sT} * p_{sR} + w_{aT} * ip_{aR}$$

$$(11) \quad \text{So that } ip_{aR} = (1/w_{aT}) - (w_{hT} * p_{hR} + w_{gT} * p_{gR} + w_{sT} * p_{sR}) / w_{aT}$$

For illustrative purposes, consider the case of a tourist who is deciding whether to visit an urban or rural region in Louisiana. BEA's published regional price parities for 2018 show consistently higher prices in the New Orleans metropolitan area compared to nonmetropolitan regions of Louisiana (91.2 vs. 52.1 for housing, 97.2 vs. 92.8 for goods and 92.6 vs. 92.5 for services). Yet New Orleans earned more than 10 times as much tourism revenue as nonmetropolitan regions of Louisiana (Charters 2019). Clearly, tourists must derive enough value from New Orleans amenities like Mardi Gras parades to offset its higher hotel prices. Based on BEA's published travel and tourism accounts (Franks and Osbourne 2019), this paper calculates the following product weights: $w_{hT} = 0.28$, $w_{gT} = 0.26$, $w_{sT} = 0.21$, and $w_{aT} = 0.25$.¹³ Given those weights and Louisiana prices, equation (11) above can be solved:

$$(12) \quad ip_{aR} = (1/0.25) - [0.28*(52.1/91.2) + 0.26*(92.8/97.2) + 0.21*(92.5/92.6)]/0.33 = 1.53$$

In other words, tourists to Louisiana value the specialized urban amenities provided by New Orleans so much that they would pay 53 percent above their current market price to keep them available. This sizable premium is sufficient to raise the average cost-of-living for tourists to nonmetropolitan Louisiana by 13 percent.

In practice, the calculation above depends on the exact regions chosen for comparison. This paper uses an OLS regression to estimate what prices would be in each region if that region had no amenities. By design, this OLS regression holds weather, jobs, and other nonprice factors constant. This analysis then imputes region-specific amenity prices using the formula solved above for Louisiana.¹⁴ Across all regions, the average price premium for unavailable amenities is 1.59. This paper will assume that the same price premium applies to all products that are completely unavailable during stay-in-place behavior.

¹³ Consistent with assumption 2, costs related to long-distance travel are excluded from the vacation budget. Next, travel accommodations are allocated to housing, shopping is allocated to goods, intracity travel and restaurant spending are allocated to services, and finally, recreation is allocated to amenities.

¹⁴ This coefficient is estimated using a weighted OLS regression of log prices on the share of employees working in North American Industry Classification System category 71. (The worker share data are taken from the Quarterly Census of Employment and Wages and top coded at 3 percent in order to reduce the influence of outliers). The regression is run separately for goods, housing, and services.