A Theory of Slack

How Economic Slack Shapes Markets, Business Cycles, and Policies

Pascal Michaillat

Draft version: January 2026

CHAPTER 3.

Prevalence, cyclicality, and social cost of slack

Before we start building our slackish model of business cycles, it is critical to look at the data to get a good sense of what we want to model. Indeed, as Kuhn (1957) explains, one of the three main qualities of a good model is to be descriptive—that is, to describe well the phenomena of interest. We therefore need to look at data from the real world to assess exactly how much slack there is out there, how slack behaves over time, and how costly slack might be. We will then incorporate these facts into the model.

Of course, everyone knows that during severe recessions such as the Great Depression or the Great Recession, a vast number of workers become unemployed. So, to understand these events, we must have a model that features unemployment in bad times.

What we will come to realize is that unemployment and slack are much more prevalent than one might think. It is not true that slack only occurs on the labor market during deep downturns: slack is a pervasive feature of modern economies, present in most markets at all times and in varying amounts. Therefore, a good macroeconomic model should feature slack in all markets, as well as fluctuations in slack.

The evidence assembled in this chapter draws on data from the United States. I make this choice because the models in this book are designed to describe the US economy. International data are not directly applicable to describe US markets and the US economy because market-level and macroeconomic outcomes are shaped by country-specific regulations, institutions, and economic customs and norms. Focusing on one country brings discipline to the data collection and model construction, but it certainly does not imply that the theory developed in this book does not apply to other countries, or that

US data are special in any way. Chapter 21 shows that many patterns of slack observed in the US economy are also found in other economies, and it argues that the theory of slack developed here could be fruitfully applied to other developed and developing economies.

3.1. Definition of economic slack

The concept of economic slack describes situations in which goods or services are available for sale but trades do not occur. When the goods or services are already produced, their costs of production are sunk, so the trades would typically generate a positive surplus. Sometimes the goods and services are not yet produced, but they are available to be produced at minimal marginal costs, so the main idea behind the concept of slack remains: trades that would generate value for sellers and buyers do not materialize.

Of course, there is no room for slack in the Walrasian model. In that model, anyone can sell anything at the market price. It is never the case that somebody would like to sell something at the market price but cannot find a buyer. Moreover, the marginal seller and buyer on a Walrasian market are indifferent between trading or not trading. Their marginal cost or marginal value for the good equals the market price, so it does not matter to them whether they trade or not. By contrast, in a world with slack, sellers are positively happy when they are able to trade, and they are distinctly hurt when they cannot trade. The same is true for buyers: they are positively happy when they are able to find the good that they are looking for.

The most famous example of slack is unemployment on the labor market. There are workers who are available and willing to work, and there are firms who are looking for workers, but the job seekers are unable to find jobs. As a result, the workers remain unproductive and their labor services are wasted.

But we also find economic slack in many other markets, not only in the labor market. For instance, in the market for services, we very often see slack. A hairdresser might be idle if no customers have come to the hair salon to get a haircut. The hairdresser is at work since the salon must remain open to attract customers; but they are idle at work until a customer arrives. We see this too in restaurants and cafes, where not all tables are always full and there are sometimes more empty seats than at other times. Depending on the number of customers sitting in their cafes and restaurant, waiters and cooks are more or less busy. Slack is also observed in hotels and airplanes, which are not always full, with hotel rooms and airplane seats sometimes remaining empty.

Slack still exists in other markets, for example in the market for goods. There, some goods are produced but cannot be sold and are thrown away: for instance food that nobody buys and that expires. But it's not just perishable goods. We also find economic slack in durable goods, such as clothes and appliances that remain unsold. Although durable goods don't go bad immediately, they depreciate over time, so stores would later have to sell them at a lower price and, eventually, discard them.

We can also see slack within firms. People employed by firms do not work at full capacity at all times; they are more or less utilized depending on the demands on their time. This sort of slack is apparent in all types of jobs. Manufacturing workers might be forced to work shorter hours if production lines are temporarily shut down due to low demand, and sometimes they might be forced to work overtime. In consulting firms, consultants are more or less busy. When business is booming, consultants work long hours on projects. But sometimes, when business is slower, consultants stay home because there isn't enough business available for them to work. So slack also affects people who are employed within firms when firms do not have business.

3.2. Prevalence of slack on the labor market

We start by documenting the prevalence of the most well-known form of slack, and the most socially costly: the unemployment of workers on the labor market.

3.2.1. Definition of unemployment

Before looking at the data, we review how unemployment is defined in the United States.

The definition involves several criteria developed by the Bureau of Labor Statistics (BLS 2023). First, the BLS isolates the part of the population that makes up the working-age civilian noninstitutional population. This group excludes individuals in the armed forces, and individuals institutionalized in jails and prisons. In addition, because we are interested in people that can work, it excludes children below 16. The resulting group consists of all potential workers. Formally, to be part of the civilian population, one must be above 16 years of age, be residing in one of the 50 US states, not be in the armed forces and in a mental or penal institution. Foreigners who reside in the United States are included.

The working-age population is then divided into two categories. The smaller category is people who are out of the labor force. People who are out of the labor force are those who do not have a job and are currently not available or interested to work: people who are retired, studying, or parenting at home.

The larger category is the labor force—everyone who is either working or available and willing to work. People who have a job are counted as employed. Formally, to be employed, you must have worked at least 1 hour in the past week as a paid employee or for your own business. People who are temporarily absent from work, on vacation or because of illness, are also counted as employed.

People who do not have a job are counted as unemployed. It is important to understand what unemployment means from a statistical perspective. There are three key criteria: not currently working; being available to work; and wanting to work. The BLS gauges desire to work by asking respondents if they have been actively searching for a job in the past 4 weeks. Actively searching for a job means using a method that has the potential to result in a job offer, such as contacting an employer, sitting for a job interview, submitting a job application, or using a placement agency. People who are temporarily laid off and expecting to be recalled to their job are also counted as unemployed.

The statistical definition of unemployment shows that the concept of "voluntary unemployment" is an oxymoron. Being unemployed is defined as wanting a job but not having one: it is by definition involuntary. Someone who does not have a job and does not want one (which is what people mean with "voluntary unemployment") is not counted as unemployed: they are out of the labor force.

3.2.2. Measurement of unemployment

How is unemployment measured in practice? Unemployment is currently measured through the Current Population Survey (CPS), which is a household survey conducted by BLS. This survey has been running since 1940: it was initially administered by the Census Bureau, and it has been administered by the BLS since 1948. Accordingly, we have a continuous measure of unemployment since January 1948. So, between January 1948 and December 2024, we compute the unemployment rate in the usual way: we take the number of job seekers measured by the BLS (2025k) from CPS, and divide it by the labor force measured by the BLS (2025a) from the CPS. This is the standard, official measure of unemployment rate, labelled U3 by the BLS. Because the unemployment rate measures the share of workers who would like to work but cannot find a job, it is measured as a share of the labor force, not of the entire population.

An issue is that, because the CPS data only start in 1948, we can't see what happened during the Great Depression—the worst recession on record. Fortunately, historians have collected data from different sources that allow us to get a picture of what was happening during that time. Between January 1929 and December 1947, we measure unemployment from the unemployment rate constructed by Petrosky-Nadeau and Zhang (2021). They extrapolate Weir (1992)'s annual unemployment series to a monthly series using various monthly unemployment rates compiled by the NBER.[1]

The resulting series is graphed in figure 3.1: it depicts the unemployment rate for the United States between January 1929 and December 2024. The shaded areas in the graph correspond to the official recession dates in the United States, which are identified by the Business Cycle Dating Committee of the National Bureau of Economic Research

[1] There is no monthly measure of unemployment between January 1890 and March 1929. Instead, the monthly unemployment fluctuations are inferred from the spread between the yields of bonds of different quality. Given these limitations, we only begin our analysis in 1929. To be able to start at the beginning of the year, we use the monthly values produced by Petrosky-Nadeau and Zhang (2021) for January, February, and March, although they are not directly computed from unemployment data.

(NBER 2023). The NBER identifies these recessions by looking holistically at numerous macroeconomic variables. Between 1929 and 2024, the NBER identifies 15 recessions.

3.2.3. Prevalence of unemployment

Over the past century, there is always some unemployment in the United States (figure 3.1).

The unemployment rate is countercyclical, rising sharply at the onset of all recessions. During the pandemic recession, the unemployment rate reached its highest level since the end of World War 2: it peaked at 13.0% (2020:Q2). During the Great Recession, the unemployment rate rose to 9.9% (2009:Q4). During the Volcker twin recessions, the unemployment rate rose to 10.7% (1982:Q4). During the first-oil-crisis recession, the unemployment rate reached 8.9% (1975:Q2). The Great Depression was on another scale: the unemployment rate reached 25.3% (1932:Q3). This amount of joblessness is something that we haven't seen since—even during the pandemic recession or Great Recession.

US recessions over the past century have had different sources, but in each one of them the unemployment rate rose. For instance, the recession in 2020 was caused by the coronavirus pandemic. The Great Recession in 2007–2009 coincided with the global financial crisis. The recession in 2001 followed the burst of the dot-com bubble. The recession in 1990–1991 followed the Iraqi invasion of Kuwait and associated oil price shock. The twin recessions in 1980–1982 are associated with the tight monetary policy imposed by Volcker to fight inflation. The recession in 1973–1975 followed the first oil crisis. The biggest recession on record, the Great Depression in 1929–1933, was triggered by the October 1929 stock market crash, followed by a collapse of the banking system. In all these recessions the unemployment rate spiked.

Although there is more unemployment during recessions, unemployment exists at all times. The lowest unemployment rate on record is 1.0%, reached at the end of World War 2 (1944:Q4). This is low but still positive. Such low unemployment was reached because of the war effort: it reduced unemployment through a combination of large-scale military production and large-scale enlistment of potential workers in the armed forces, which shrank the labor force. The World War 2 experience is typical: wartime generally leads to low unemployment. The unemployment rate fell to 2.6% at the end of the Korean War (1953:Q2), and it dropped to 3.4% in the middle of the Vietnam War (1969:Q1).

Overall, between 1929 and 2024, there are always some unemployed workers in the US economy. The unemployment rate averages 6.4% over the period. The unemployment rate reached its highest level on record, 25.3%, during the Great Depression and its lowest level on record, 1.0%, at the end of World War 2 (1944:Q4).

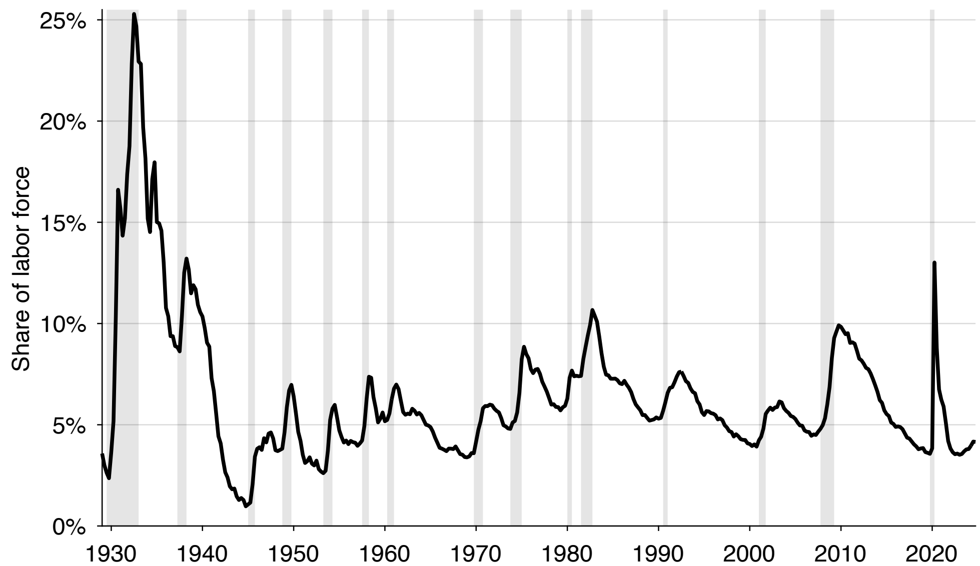


FIGURE 3.1. Unemployment in the United States, 1929–2024

The unemployment rate is a quarterly series computed from monthly, seasonally adjusted data produced by Petrosky-Nadeau and Zhang (2021) and the BLS (2025k,a). Shaded areas indicate recessions dated by the NBER (2023).

3.2.4. Additional measures of unemployment

The concept of unemployment is meant to measure slack on the labor market. So in theory unemployment should comprise anyone who is available and willing to work but unable to find a job. The empirical challenge is to determine who wants to work. Reasonably, the BLS decided that somebody who wants to work is bound to search for a job, so the BLS asks people whether they have been searching for a job to determine whether they are unemployed. However, people search with different intensity and methods, maybe reflecting different willingness to work. The standard unemployment rate (U3) only counts as unemployed people who have been actively searching in the past 4 weeks (searching using a method that has the potential to result in a job offer). So there are workers who have been searching for a job in the past year but not in the past month who are not counted as unemployed. The job seekers might have stopped searching in recent weeks not because they do not want a job but because they could not find any appropriate jobs and lost hope. Similarly, there are people who have been searching for a job passively instead of actively who are not counted as unemployed. These job seekers have been using methods that could not result in a job offer unless additional steps are taken, for instance simply looking at job postings. These people may not have contacted firms because they did not see a good match, or because they were in training. To include all these job seekers

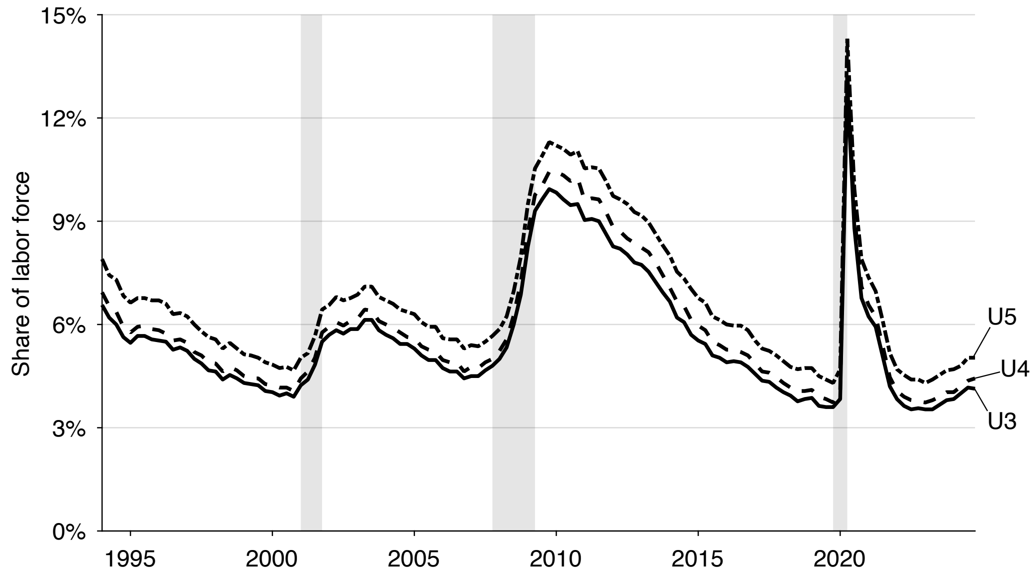


FIGURE 3.2. Alternative measures of unemployment in the United States, 1994–2024

The unemployment rates are quarterly averages of monthly, seasonally adjusted series computed by the BLS (2025l,i,j). Shaded areas indicate recessions dated by the NBER (2023).

into unemployment as well, the BLS developed additional measures of unemployment to count such workers.

The unemployment concept U4 includes everyone in the standard unemployment concept U3, plus discouraged workers. These are people who are available to start a job, have been actively searching for a job in the past 12 months, but have not been actively searching in the past 4 weeks because they became discouraged about their job prospects. When asked why they did not look for work during the last 4 weeks, discouraged workers respond for instance that "There are no jobs available," or "They have been unable to find work in the past." They are not counted in U3 because they did not actively search for work in the last 4 weeks.

The unemployment concept U5 includes everyone in U4 plus marginally attached workers. These are people who are available to start a job, have been actively searching for a job in the past 12 months, but have not been searching in the past 4 weeks for other reasons than discouragement about their job prospects. When asked why they did not look for work during the last 4 weeks, these workers respond for instance that they could not search because of family responsibilities, childcare, or illness. These additional workers are not classified in U3 because they did not actively search for work in the last 4 weeks; they are not classified in U4 because they were not discouraged about their job prospects.

The main takeaway is that the U4 and U5 rates are very close to the standard, U3 rate (figure 3.2). Between 1994 (when the U4 and U5 concepts were introduced) and 2024, the U3 rate averages 5.6%, the U4 rate averages 5.9%, and the U5 rate averages 6.6%. So on average the discouraged workers make up only 0.3% of the labor force, and the marginally attached workers make up just 1% of the labor force. Furthermore, these slivers of the labor force do not vary much over the business cycle. The distance between the U3 and U4 rates is always less than 0.8pp and the distance between the U3 and U5 rates is always less than 1.5pp.

A final form of unemployment are unemployed hours—originating from workers who work part time, although they were available and willing to work full time. Statistically, working part time means working less than 35 hours a week, while working full time means working 35 hours or more. If a worker is willing to work full time but is only able to find a part-time job, some of the hours that they are willing to supply are unemployed. However, such workers (part of the U6 concept of unemployment) are only a small sliver of the labor force. In 2024:Q4, only 0.7% of the labor force were working part time because they could not find a full-time job (BLS 2025b,a). And then for each worker, only a part of the 35 hours that they could work was unemployed.

3.3. Prevalence of slack on the product market

We have seen that slack is prevalent on the labor market. But slack is not limited to the labor market; it is also prevalent on the product market. Indeed, producers are never able to sell all the goods and services that they could potentially produce to customers.

3.3.1. Prevalence of unsold goods

Slack takes several forms on the product market. The most basic form is unsold goods, such as unsold food. Unsold food by farmers and manufacturers, and in grocery stores and restaurants, generate a vast amount of food waste in the United States (ReFED 2025). In 2023, 31% of the US food capacity (in tons) is surplus: either unsold or unused by businesses, or uneaten at home. The value of the food unsold by farms, manufacturers, restaurants, and grocery stores represents 5% of the value sold.

Of course, it is not only food that US firms have difficulties in selling. Any sort of output is difficult to sell. The Occupational Employment Survey (OES) run by the BLS indicates that 11% of US workers are in occupations devoted to sales, including retail salespersons, sales representatives, and advertising agents (Gourio and Rudanko 2014). These workers are used by firms to sell their products, and indicate that it is hard for firms to find customers (Hall 2012). Relatedly, based on a survey of 4,000 firms run by APQC, Fernandez-Villaverde et al. (2025) report that 7.5% of firms' revenue is devoted to attracting customers.

When firms produce durable goods that they cannot sell, they generate unsold inventory. Indeed if firms keep producing durable goods when there is less demand for them, the unsold goods just pile up in inventory. We do see inventories swell up when firms are not able to sell their goods, and inventories shrink when demand is brisk (Bils and Kahn 2000).

3.3.2. Prevalence of idle capacity

Another form of slack on the product market is idle capacity in firms: capacity that is available and ready to produce goods and services, but remains unused because of a lack of demand. It is a type of slack that is less commonly discussed but still very prevalent, as we see from data collected by the Institute for Supply Management (ISM 2025). The ISM keeps track of the "operating rate", both for manufacturing and nonmanufacturing industries. The operating rate indicates the actual production level of firms as a fraction of the maximum production level that these firms could have achieved given their current capital and labor. From this operating rate, we can create a rate of idleness, which is just 1 – operating rate. The idleness rate is the share of productive capacity that is idle because of a lack of demand: the amount of goods or services not sellable and therefore not produced, as a fraction of the total capacity of a firm given current capital and labor.

In the United States, we find that some capacity is idle at all times (figure 3.3). Between 1990 and 2024, the rate of idleness in the manufacturing sector averages 17.3%. And between 2000 and 2024, the rate of idleness in nonmanufacturing sectors averages 13.9%. This means that usually, given their capital and labor, firms could sell about 15% more than what they actually sell, if they had the demand for it.

The rate of idleness is the product-market equivalent of the rate of unemployment. Perhaps surprisingly, the rates of idleness in the manufacturing and nonmanufacturing sectors are much higher than the rate of unemployment. There are several ways to see this. The average rates of idleness are higher than the average rate of unemployment rate between 1990 and 2024, which is only 5.7%. The manufacturing rate of idleness is always above 10% and the nonmanufacturing rate of idleness is always above 8%. Both lower bounds on idleness correspond to already significant amounts of unemployment. Last, we can compare figure 3.1 to figure 3.3: we can see that at any time the unemployment rate is below the rates of idleness. The data show us that more labor is idle within firms than outside them: product market slack is a critical phenomenon.

Just like the rate of unemployment, the rates of idleness are sharply countercyclical, climbing in recessions. Idleness in the manufacturing sector peaked at 33.0%, during the Great Recession (2009:Q2). Manufacturing idleness was also elevated during the other recessions in the data: the idleness rate reached 20.6% after the Iraq War recession (1991:Q2), 22.5% after the dot-com bubble recession (2001:Q4), and 24.1% after the pandemic re-

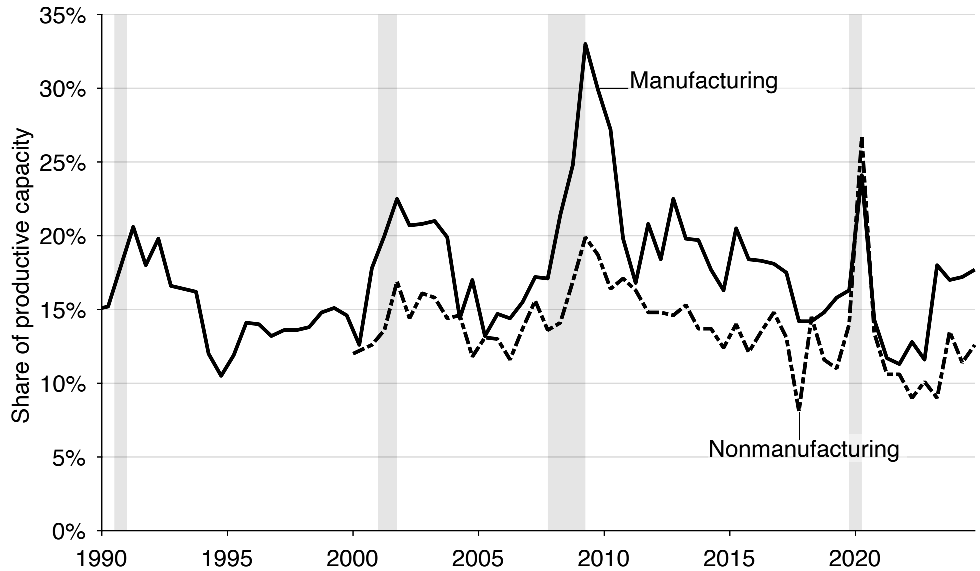


FIGURE 3.3. Idle capacity in the United States, 1990–2024

The idleness rates are quarterly series constructed by interpolating the semiannual operating rates measured by the ISM (2025). For nonmanufacturing sectors, the operating rate is only available after 2000. Shaded areas indicate recessions dated by the NBER (2023).

cession (2020:Q2). Slack in the nonmanufacturing sectors peaked at 26.7%, during the pandemic recession (2020:Q2). Nonmanufacturing idleness also reached 19.9% after the Great Recession (2009:Q2) and 16.9% after the dot-com bubble recession (2001:Q4). We see that idleness is a much bigger problem during recessions. We also see that the Great Recession was relatively worse for manufacturing sectors, while the pandemic recession was relatively worse for nonmanufacturing sectors.

3.3.3. When product market slack bleeds into the labor market

We have just seen that people employed by firms are idle some of the time at work because firms do not have enough business. In that case product market slack materializes as idleness at work. If workers are sent home by firms and their hours reduced, then product market slack materializes in another way: as full-time workers being forced to work part time because their employers do not have sufficiently many customers. These workers are counted as employed, but they are flagged as involuntary part-time workers in the CPS by the (BLS 2025c). Their usual hours of work are above 35 hours a week but they are now forced to work less than 35 hours because of unfavorable business conditions or low seasonal demand.

Again, this is a form of product market slack, since the issue is that the workers' labor

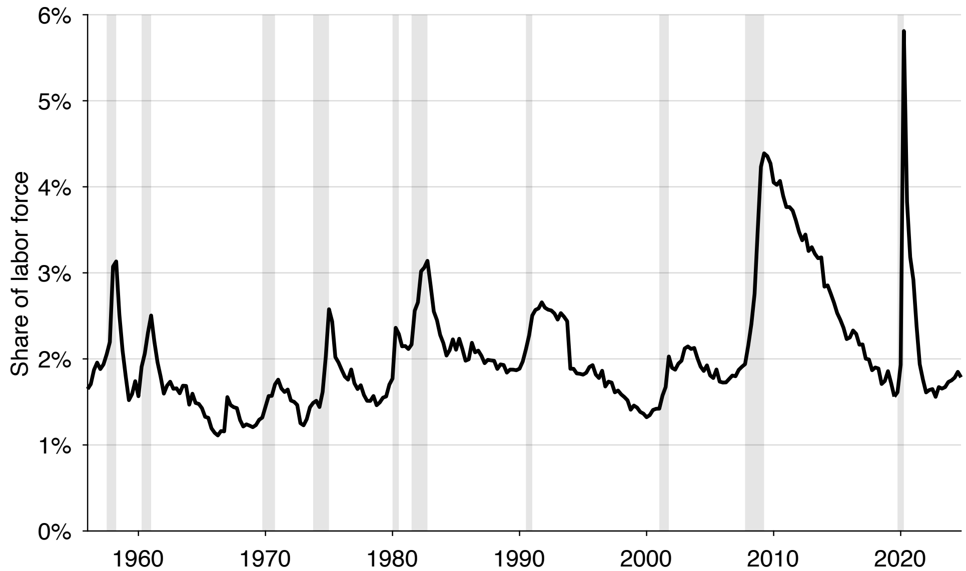


FIGURE 3.4. Workers forced to reduce hours because of product market slack in the United States, 1956–2024

The share of workers forced to reduce hours is a quarterly series computed from monthly, seasonally adjusted data produced by the BLS (2025c,a). Shaded areas indicate recessions dated by the NBER (2023).

services cannot be sold to customers—not that workers cannot sell their labor to firms. These workers are another component of the U6 unemployment concept measured by the (BLS 2023), but they should not be interpreted as labor market slack: they really represent product market slack.

We see that many people are working part-time because of slack on the product market (figure 3.4). On average between 1956 and 2024, 2.1% of the labor force is working less than full time because of product market slack; that share is always above 1%. Just like the slack rate in figure 3.3, that share of workers is sharply countercyclical: much higher in bad times than in good times. During the Great Recession, the share spiked to 4.4% (2009:Q2); during the pandemic recession, it spiked to 5.8% (2020:Q2).

3.4. Coexistence of sellers and buyers

We have observed slack on the labor market in the form of unemployed workers and slack on the product market in the form of idle capacity. To explain these patterns, we could simply use a nonclearing Walrasian model—a Walrasian model with a non-market-clearing price. With an above-market-clearing price in the product market, there would be excess supply of goods and services, and we could explain why there are firms that have goods and services that are not sold. With an above-market-clearing wage in the labor market, there would be excess supply of labor, and we could explain why there are workers who want to work but are not employed.

However, the world is more complicated than that because just as there are sellers who are unable to sell their goods or services, we see buyers who are unable to purchase goods or services. The coexistence of sellers and buyers is inconsistent with the nonclearing Walrasian model. In a situation of excess supply, such a model can explain the existence of slack. But in excess supply, buyers are on their demand curves, so they are able to purchase the amount of goods or services that they desire at the prevailing price. In other words, all buyers can successfully and seamlessly purchase the amount of goods and services that they desire. So the nonclearing Walrasian model cannot explain the coexistence of sellers and buyers that have not been able to trade.

We now review evidence of this conundrum. We start with the labor market, where the presence of job vacancies has been well documented. We then turn to the product market, where the evidence is less readily available.

3.4.1. Coexistence of job seekers and vacant jobs

On the labor market, not only do we always have unemployed workers trying to find jobs, but we also always have firms trying to fill vacant jobs. The presence of vacant jobs is the concrete manifestation that firms are looking to hire labor.

How can we assess whether firms want to hire workers at any point in time? Well, we have to look at the number of job vacancies that firms report. Job vacancies are measured through the Job Openings and Labor Turnover Survey (JOLTS), which is a firm survey conducted by the BLS since January 2001.[2] The definition that the BLS (2024) adopted for job vacancy parallels the definition of an unemployed worker. There are three conditions. First, a specific position exists, and there is work available for that position. Second, the job must start within one month. And third, there is active recruiting for that position for workers outside the establishment. So each vacant position is associated with recruiting within firms, which ensures that firms are actively looking for new workers. Hence, between January 2001 and December 2024, we compute the vacancy rate from the number of job openings measured by the BLS (2025d) from the JOLTS. We divide the number of job openings by the size of the labor force, which is measured by the BLS (2025a) from the CPS, to express the number of vacant jobs as a share of the labor force.

There are no governmental measures of job vacancies in the United States before

[2]To best align CPS and JOLTS data, we shift forward by one month the number of job openings from JOLTS. For instance, we would assign to October 2024 the number of job openings that the BLS assigns to September 2024. The motivation for this shift is that the number of job openings from the JOLTS refers to the last business day of the month (Monday 30 September 2024), while the labor force from the CPS refers to the Sunday–Saturday week including the 12th of the month (Sunday 6 October 2024 to Saturday 12 October 2024). So the number of job openings refers to a day that is closer to next month's CPS week than to the current month's CPS week. With this shift, the JOLTS conveniently starts in January 2001 instead of December 2000.

2001, but other organizations have been collecting data on vacant jobs before that, and researchers have transformed these data into vacancy series. Between January 1951 and December 2000, we use the vacancy rate produced by Barnichon (2010) from the Conference Board's help-wanted advertising index. The Conference Board index aggregates help-wanted advertising in major metropolitan US newspapers. Given the shift from print advertising to online advertising with the advent of the internet, the Conference Board index needs to be adjusted in the 1990s, which Barnichon (2010) has done. Between January 1929 and December 1950, we use the vacancy rate produced by Petrosky-Nadeau and Zhang (2021) from MetLife's help-wanted index. This index aggregates help-wanted advertisements from newspapers across major US cities, and reliably proxies for job vacancies (Zagorsky 1998).[3]

A first natural question is whether help-wanted indices proxy well for job vacancies. Comparing them to local data on job vacancies and other available evidence, (Abraham 1987) and (Zagorsky 1998) find that both the Conference Board index and the MetLife index proxy well for job vacancies. A second natural question is how the number of job vacancies can be recovered from an index? This is done by scaling the indexes to eventually match the number of job vacancies at the beginning of the JOLTS: the Conference Board index is scaled to align with the JOLTS vacancy rate in January 2001, and the MetLife index is scaled to align with the scaled Conference Board index in January 1951. Scaling effectively translates the indexes into vacancy rates.

Next, we splice the three vacancy series to create a continuous vacancy rate covering January 1929–December 2024 (figure 3.5). The series is procyclical, rising sharply in expansions. In the recovery from the coronavirus pandemic, the vacancy rate reached its highest level on record: it peaked at 7.2% (2022:Q2). Just before the Great Recession, the vacancy rate reached 3.1% (2007:Q2). Just before the burst of the dot-com bubble, the vacancy rate peaked at 4.1% (2000:Q1). Before the Volcker recessions, the vacancy rate was even higher, spiking at 5.1% (1979:Q2). Job vacancies are generally elevated in wartime: the vacancy rate reached 6.7% at the end of World War 2 (1945:Q1), 4.3% during the Korean War (1953:Q1), and 5.1% during the Vietnam War (1969:Q1).

While it is true that job vacancies exist in large numbers during expansions, vacant jobs exist at all times, which tells us that firms are always looking for some workers, just like some workers are always looking for jobs. Even in recessions, the vacancy rate remains positive. The lowest vacancy rate on record is 0.7%, reached in the depth of the Great Depression (1933:Q1). This is a very low number, but still positive. During the Great Recession, the vacancy rate dwindled to 1.5% (2009:Q3). The vacancy rate bottomed at 2.2% after the dot-com bubble recession (2003:Q2) and at 2.3% after the Volcker twin recessions (1982:Q4). The vacancy rate was also extremely low in the recessions that

[3] Petrosky-Nadeau and Zhang (2021) produce a vacancy series that starts in 1919, but we start the vacancy series in 1929 to align it with the unemployment data from figure 3.1.

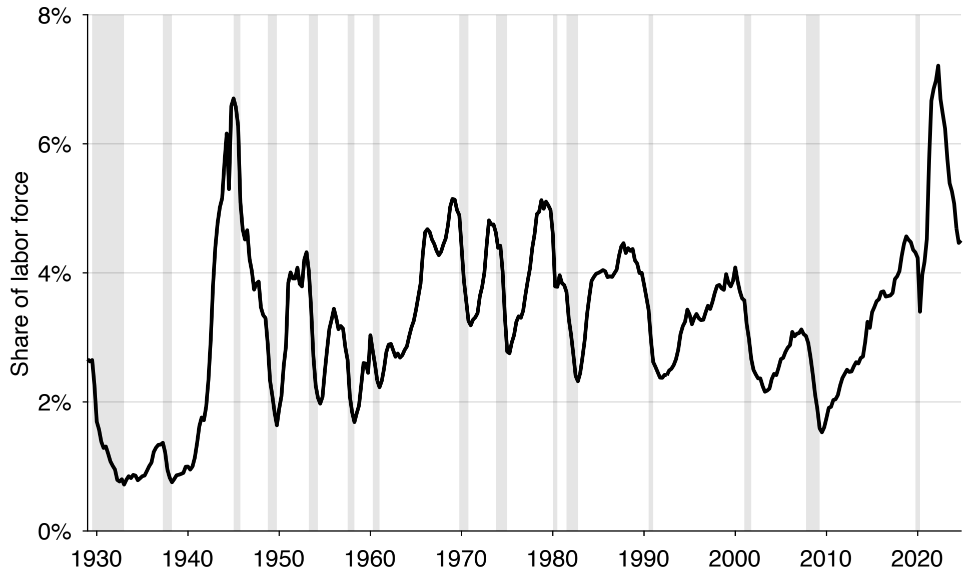


FIGURE 3.5. Job vacancies in the United States, 1929–2024

The vacancy rate is a quarterly series computed from monthly, seasonally adjusted data produced by Petrosky-Nadeau and Zhang (2021), Barnichon (2010), and the BLS (2025d,a). Shaded areas indicate recessions dated by the NBER (2023).

followed the Great Depression: 0.8% after the 1937–1938 recession (1938:Q2) and 1.6% after the 1948–1949 recession (1949:Q4).

Overall, between 1929 and 2024, the vacancy rate averages 3.2%. The vacancy rate reached its highest level on record, 7.2%, during the recovery from the pandemic and its lowest level on record, 0.7%, during the Great Depression. The bottom line is that, just as there always are unemployed workers, there always are vacant jobs.

3.4.2. Beveridge curve

We have seen in figures 3.1 and 3.5 that the number of job seekers is countercyclical while the number of vacant jobs is procyclical. This implies that the unemployment and vacancy rates are negatively related. This negative relationship between unemployment and vacancy rates corresponds to the Beveridge (1944) curve: a key empirical relationship that guides our modeling and policy design throughout the book.

The Beveridge curve appears clearly on a scatter plot with unemployment rate on the horizontal axis and vacancy rate on the vertical axis (figure 3.6). Here to illustrate, we only use recent data, between 2000 and 2019. We stop before the pandemic to simplify the picture. The Beveridge curve says that when the economy is in a slump, there are a lot of job seekers and few vacant jobs. Good examples of such situations are 2003:Q2,

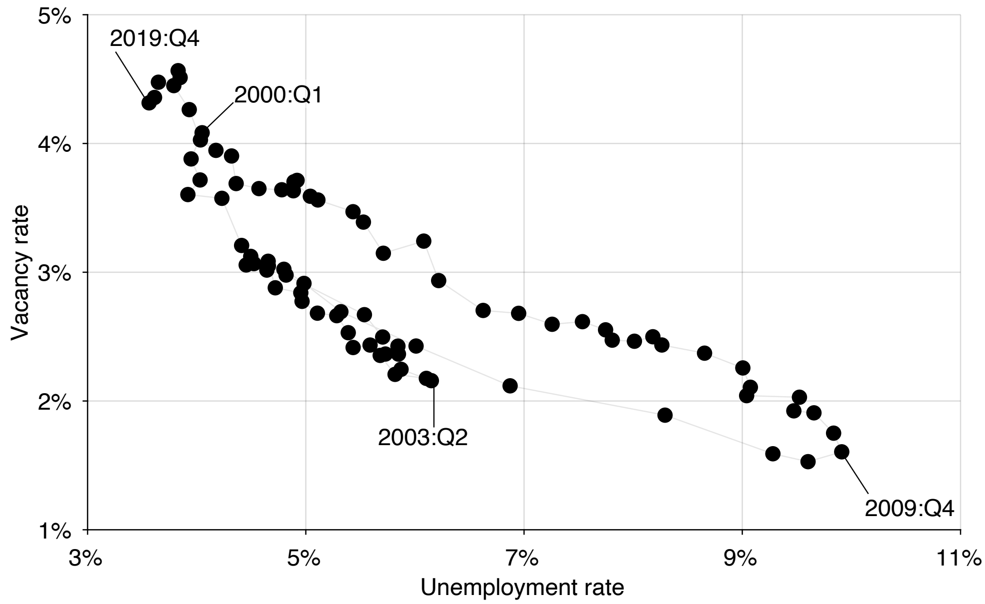


FIGURE 3.6. Beveridge curve in the United States in recent decades, 2000–2019

The unemployment rate comes from figure 3.1 while the vacancy rate comes from figure 3.5.

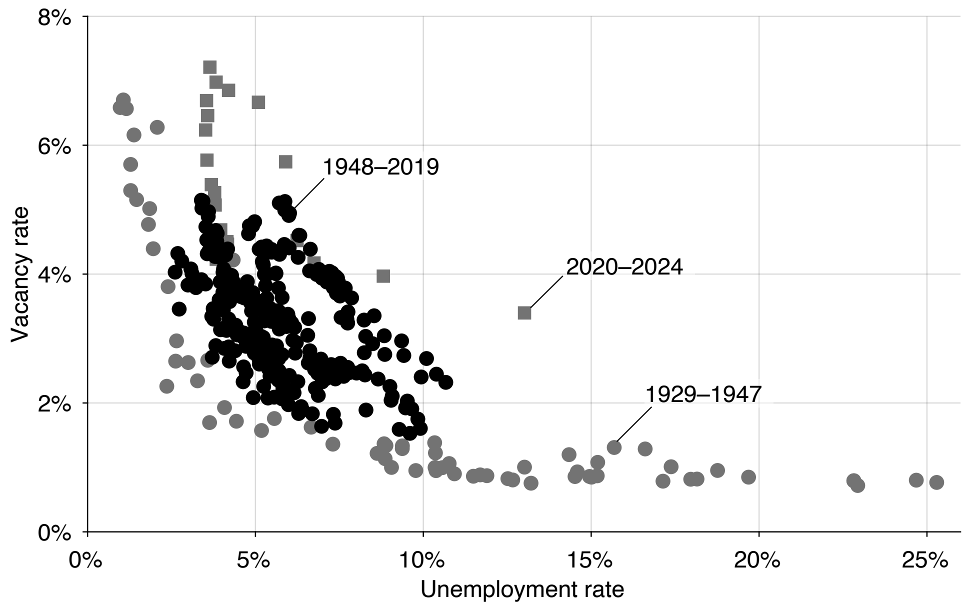
when the unemployment rate reached 6.2% and the vacancy rate fell to 2.2%, and 2009:Q4, when the unemployment rate peaked at 9.9% and the vacancy rate plummeted to 1.6%. Conversely, when the economy is in a boom, there are few job seekers and many vacant jobs. Such a situation occurred in 2019:Q4, when the unemployment rate dipped to 3.8% and the vacancy rate reached 4.3%.

Although the Beveridge curve was first observed in Great Britain (Dow and Dicks-Mireaux 1958), it holds remarkably well in the United States (Blanchard and Diamond 1989; Elsby, Michaels, and Ratner 2015).

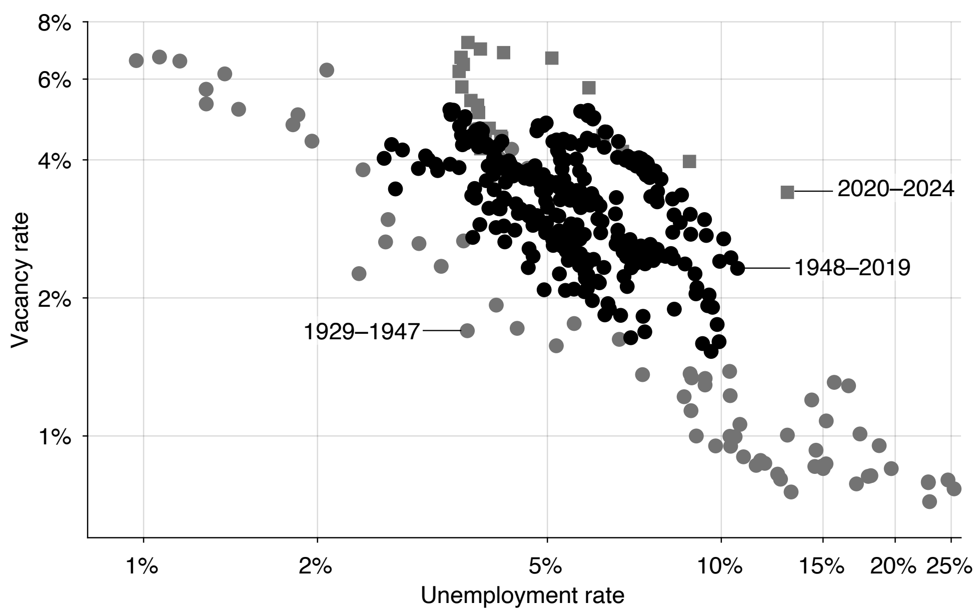
To illustrate, figure 3.7 displays the Beveridge curve for the entire period of our data, 1929–2024. The figure offers two displays: a regular display (figure 3.7A) and a display on a log scale (figure 3.7B), which is useful to show that the Beveridge curve is isoelastic—that there is a linear relationship between log vacancy and log unemployment.

The figure distinguishes three subperiods. The initial period, 1929–1947, was extremely volatile, not least because it experienced two dramatic events, the Great Depression and World War 2. Data available for the period are also the noisiest since neither unemployment nor job vacancies were measured by the government. Around the middle of the Great Depression and at the end of World War 2, the Beveridge curve is subject to two large, outward shifts. These shifts are hard to discern on this figure but will be seen clearly in chapter 15.

In the next, postwar period, 1948–2019, the Beveridge curve is well-behaved. The US



A. Regular scale



B. Logarithmic scale

FIGURE 3.7. Beveridge curve in the United States, 1929–2024

The unemployment rate comes from figure 3.1 while the vacancy rate comes from figure 3.5.

Beveridge curve is stable for long periods of time, before shifting inward or outward after a decade or more (Michaillat and Saez 2021, figure 5). The structural breaks in the curve are of modest size compared to those that occurred in the 1929–1947 period. The economy is always tightly on the Beveridge curve.

Finally, the last subperiod corresponds to the coronavirus pandemic and its aftermath, 2020–2024. The pandemic shattered the US labor market and dramatically shifted the Beveridge curve outward. The Beveridge curve slowly recovered from the pandemic shift over the next few years and it only came back close to its pre-pandemic position in 2024.

In fact, unemployment and vacancy rates appear not only to be negatively related, but to be the inverse of each other. So doubling the unemployment rate cuts the vacancy rate in half, and conversely, doubling the vacancy rate cuts the unemployment rate in half. Mathematically, the property that the unemployment rate and vacancy rate are inversely related implies that the Beveridge curve is a rectangular hyperbola:

$$vu = A,$$

where $A \in (0, 1)$ is a constant. The rectangular hyperbola can be rewritten $v = A/u$, so we can see that the elasticity of the vacancy rate with respect to the unemployment rate along the Beveridge curve is -1.

It is possible to establish that the Beveridge curve is close to a rectangular hyperbola formally. This can be done by estimating the elasticity of the vacancy rate with respect to the unemployment rate along each of its branch. An elasticity of -1 corresponds to a rectangular hyperbola. It turns out that during the postwar period, the elasticity of the Beveridge curve on each branch remains between -0.84 and -1.02, so never far from -1 (Michaillat and Saez 2021, figure 6).

It is possible to make the case for a hyperbolic Beveridge curve without introducing structural breaks and looking to branches in isolation. The idea is to remove a very slow-moving trend from the unemployment and vacancy rates to eliminate the decennial movements of the Beveridge curve, and to then estimate the elasticity of the detrended vacancy rate with respect to the detrended unemployment rate. To be precise, we remove from log unemployment rate a slow-moving trend obtained from a Hodrick-Prescott (HP) filter with smoothing parameter 10,000.[4] We do the same to the log vacancy rate. We then regress detrended log vacancy rate on detrended log unemployment rate. We focus on the 1948–2019 period because the large shifts in the Beveridge curve before and after that period are difficult to handle. We find that the slope is exactly -1.00 with a good fit, $R^2 = 0.87$ (figure 3.8). Thus, with detrended variables, the US Beveridge curve is a perfect rectangular hyperbola over seven decades, 1948–2019.

[4] Appendix A provides an introduction to the HP filter and explains the choice of the smoothing parameter. We use the HP filter with that smoothing parameter throughout the book, whenever detrending is required.

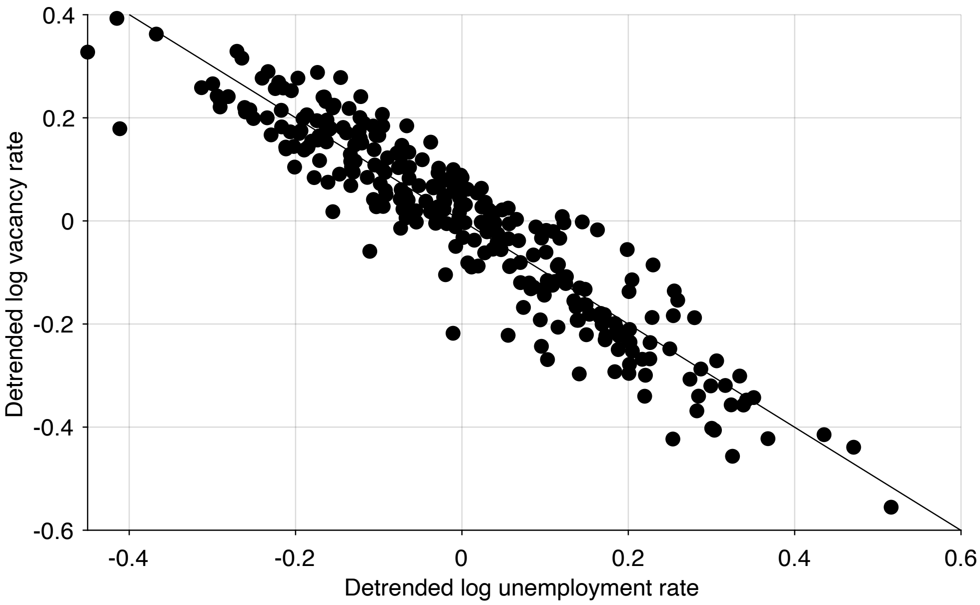


FIGURE 3.8. The US Beveridge curve is a rectangular hyperbola

The unemployment rate comes from figure 3.1 while the vacancy rate comes from figure 3.5. The figure plots the logarithm of the vacancy rate against the logarithm of the unemployment rate, both detrended using an HP filter with smoothing parameter 10,000. The data are for 1948–2019.

3.4.3. Coexistence of product sellers and buyers

On the product market, buyers trying to purchase goods and services always coexist with goods and services for sale, and sellers trying to sell these items.

For example, US consumers spent a significant amount of time shopping, driving to shops, researching their shopping, and waiting in line at shops. Time-use data recorded by the BLS through the American Time Use Survey (ATUS) show that on an average day between 2003 and 2012, US consumers devote 42 minutes to shopping, including 18 minutes traveling to shops, 8 minutes buying groceries, gas, and food, 15 minutes researching and buying consumer goods and services, and 1 minute waiting at shops (Petrosky-Nadeau, Wasmer, and Zeng 2016, table 1).

A first reason why buying takes time is that it is difficult to find the appropriate good that fits one's needs. This difficulty manifests itself in the large number of goods that are returned after purchase because they did not meet the buyer's needs. In 2020 in the United States, $428 billion of merchandise were returned to sellers—a value representing 10% of retail sales (Janssen and Williams 2024, p. 387). For online retail only, $102 billion of merchandise were returned, representing 18% of sales.

Another reason why buying takes time is that goods are not always available in shops. Using the microdata underlying the Consumer Price Index, Bils (2016, table 1) finds that temporary stockouts are quite common: the average stockout rate is 4.6% across 180 categories of goods between 1988 and 2009. That is, about 5% of visits to a store do not result in a purchase because the desired product is unavailable. Taylor and Fawcett (2001, figure 1) surveyed the availability of 40 items (half advertised and half not advertised) across 20 US stores for 4 weeks. They find that for advertised items, stockouts occur on 12%–16.5% of the visits; for regular items, stockouts occur on 6.1%–7.6% of the visits. Stockouts are also prevalent for online retailers. Jing and Lewis (2011, table 1) find that 25.4% of orders placed to an online retailer were imperfectly filled—some of the items that were ordered could not be shipped to the customer. The value of the items in stockout represents 9.7% of the total value of the orders. The inconvenience imposed by stockouts on buyers is visible in how they respond: customers are generally upset when they drive to a shop, expecting to buy a product, but are unable to find it (Taylor and Fawcett 2001). In a field experiment conducted in a mail-order catalog, Anderson, Fitzsimons, and Simester (2006) find that customers subjected to a stockout reduce their spending on other items in the order, and reduce long-run spending on the catalog's products.

Of course, the activity of purchasing goods and services is not limited to households. Firms are also constantly trying to purchase goods and services from other firms. In fact, the amount of labor devoted by firms to source goods and services might not be very different from the amount of labor devoted to recruiting. According to the OES, on average between 1997 and 2012, 560,600 workers were employed in buying, purchasing, and procurement occupations while 543,200 workers were employed in occupations involving recruitment, placement, screening, and interviewing (Michaillat and Saez 2015, figure 2B). We do not have a measure of product demand like job vacancies, but given the OES numbers, it's clear that firms devote significant resources to purchasing goods and services.

3.4.4. Long-term relationships on the labor and product markets

The difficulties in matching sellers and buyers that create slack on most markets also incentivize sellers and buyers to form long-term relationships to mitigate these very difficulties. Accordingly, we see that long-term relationships are extremely common on the labor and product markets.

In the United States, the vast majority of workers are engaged in long-term employment contracts with firms. In CPS data for 1997, Kalleberg (2001, table 8.2) finds that 71% of men and 62% of women are engaged in standard employment relationships. In such a relationship, the work is full time and the employment relationship is assumed to continue for a substantial period or indefinitely. In addition, 8% of men and 22% of women are engaged in regular part-time employment, which is not full-time but is also expected to continue for a substantial period or indefinitely. So overall 79% of employed men and

84% of employed women are in long-term employment relationships. The main types of employment that are not long-term are self-employment and independent contracting (although these workers might be in long-term customer relationships with firms). These numbers have not changed much between the 1960s and 1990s (Kalleberg 2001, table 8.3). Between the 1990s and 2010s, the number of workers in alternative work arrangements increased by a few percentage points, driven partly by the emergence of the gig economy (Katz and Krueger 2019, table 2).

Long-term relationships between customers and suppliers are common. Blinder et al. (1998, Table 4.12) report that on average in US firms between 1990 and 1992, 85% of sales go to long-term customers. Dube, Hitsch, and Rossi (2010) documents that consumers have a higher probability of choosing products that they have purchased in the past—thus remaining loyal to the product and brand that they patronized in the past. Analyzing data on foreign trade and transactions from the Census Bureau, Monarch and Schmidt-Eisenlohr (2023, table 1) find that more than 80% of US imports occur through long-term relationships.

In fact, a broad share of transactions on the product market are conducted under explicit contracts that link sellers and buyers over time. In BLS data on contractual arrangements between firms trading intermediate goods, Goldberg and Hellerstein (2011) find that one-third of all transactions are conducted under contract across industries, for both goods and services. Fernandez-Villaverde et al. (2025, figure 1) confirm that most customer-supplier relationships in the United States are long term, with an average duration of 3.5 years. Macchiavello (2022, p. 340) reviews a wide range of evidence and concludes that

> Many—and perhaps most—transactions between firms occur in long-term relationships rather than in spot markets, as typically theorized in economic models.

3.5. Cyclicality of slack

This book is about business cycles. In it we will see that fluctuations in slack are a central part of business cycles. But what are business cycles? Here is a standard definition of business cycles, proposed by Burns and Mitchell (1946, p. 3):

> A cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with amplitudes approximating their own.

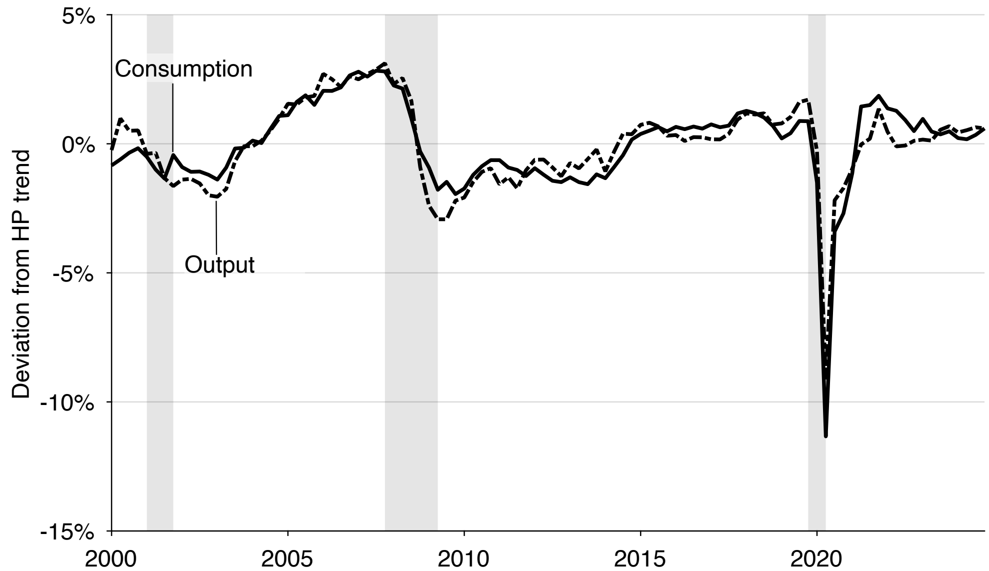


FIGURE 3.9. Fluctuations in consumption and output in the United States, 2000–2024

Output is real gross domestic product measured by the BEA (2025b). Consumption is real personal consumption expenditure measured by the BEA (2025c). The original quarterly, seasonally adjusted series are detrended by applying to their logarithms a HP filter with smoothing parameter of 10,000. Shaded areas indicate recessions dated by the NBER (2023).

The typical measures of activity used to study and describe business cycles include industrial production, output, and consumption. They all move in tandem, and go up and down by a few percent points from trend at each recession and expansion (Stock and Watson 1999).

The business cycle fluctuations to be explained are presented on figure 3.9. We recognize the typical pattern: output and consumption are above trend in expansion, and below trend in recessions. In the 21st century, output and consumption move essentially in tandem (this was not necessarily the case before). In fact, between 2000 and 2024, the correlation between detrended output and consumption is 0.92.

Figure 3.9 addresses a possible concern about the approach taken in the book. Output is the sum of private and public consumption, private and public investment, and net exports. The models in the book abstract from imports and exports, and from capital and investment. While one might worry that a model abstracting from trade and investment could not explain output fluctuations, the figure shows that private consumption moves so closely with output that our focus is well-suited to the task.

The goal of business cycle research is to develop a model that can explain the fluctuations described by Stock and Watson (1999). We can postulate two possible sources of business cycle from a simple slack identity. By definition, slack is the share of the economy's productive capacity that is either not used or not sold, so

$$\text{output} = (1 - \text{slack}) \times \text{productive capacity}. \tag{3.1}$$

This identity shows that there are two possible and nonexclusive sources of output fluctuations: fluctuations in productive capacity and fluctuations in slack.

There are three inputs into productive capacity. First is the capital stock. Second is the labor force: the share of the working-age civilian population that is available and willing to work. Third is technology: the blueprint to the production process, which shows how to combine capital and labor effectively. These inputs are combined through a production process to generate the productive capacity. We will see in the next sections that all these inputs, and therefore productive capacity, are broadly acyclical. This will leave fluctuations in slack as the main explanation for business cycle fluctuations.

3.5.1. Capital is broadly acyclical

How much does the capital stock vary over time and, in particular, over the business cycle? This is a fairly easy question to answer: we just need to look at capital stock at constant national prices for the United States graphed from 1950 to 2019 (University of Groningen and University of California–Davis 2023). It is clear that the capital stock is growing over time, but notice that the growth of the capital stock is extremely smooth—it is essentially unaffected by recessions or by the business cycle in general. This is not a new finding. If we go back to the first chapter of the main textbook of the Real Business Cycle literature, *Frontiers of Business Cycle Research*, one of the findings is that capital stock fluctuates much less than output and is largely uncorrelated with output (Cooley and Prescott 1995). Thus, we conclude that the US capital stock is acyclical.

3.5.2. Labor force is broadly acyclical

Next, how much does labor supply vary over the business cycle? The labor force is the labor supply. It is composed of the members of the working-age civilian population who want to work. Mathematically, the labor force is the product of the working-age civilian population and the labor force participation rate.

The working-age civilian population, of course, is growing at a very stable rate and not subject to cyclical fluctuations (BLS 2025h).

Then, we need to look at the share of the civilian population that wants to work: the labor force participation rate. This is the main decision that people make in the real world: whether to participate in the labor force or not.

It turns out that the participation rate doesn't really vary over the business cycle. The participation rate is molded by medium-run fluctuations that do not have much to do with the business cycle. Until the 1970s, the rate was fairly stable with some small fluctuations (BLS 2025e). There was then a big increase in the participation rate between the mid 1960s and the mid 1990s as women entered the labor force in large numbers (BLS 2025g). After the mid 1990s, there was a plateau followed by a decline in the participation rate from the 2000s. The participation rate for men has been declining since the 1950s, but this decline was more than compensated until the 1990s by women entering the labor force (BLS 2025f).

The medium-run forces might make it difficult to ascertain that the labor force participation rate is truly acyclical—although by looking separately at the participation rates for men and women, it is quite clear that they are acyclical (BLS 2025f,g). In any case, to be completely sure, researchers have explored the cyclicality of the participation rate with statistical techniques. Using US data covering 1946–1954, Rees (1957, p. 32) does not find evidence of the discouraged-jobseeker theory. In US data covering 1960–2006, Shimer (2009, p. 294) finds that the labor force participation rate is acyclical. Similarly, using US data spanning 1976–2009, Rogerson and Shimer (2011, pp. 624–625) find that over the business cycle, the labor force participation rate is nearly constant. Running a vector autoregression on US data for 1976–2016, Cairo, Fujita, and Morales-Jimenez (2022, figure 1C) find that the impulse response of the labor force participation rate to a positive productivity shock (the typical shock in the business cycle literature) is 0 for 2 years, and never significantly different from 0 after that.

It is true that labor force participation dropped around the Great Recession (Erceg and Levin 2014), but the decline was primarily caused by population aging and other trends that preceded the recession (Aaronson et al. 2014; Krueger 2017). The only recession that led to a big change in the participation rate was the pandemic recession. When the pandemic started, there was a large drop in the participation rate, from 63% down to 60%. This drop was something we had never seen before. Workers decided to drop out of the labor force in large numbers because it became dangerous to work, and school closures imposed new childcare obligations. The participation rate recovered once working became safe again and schools reopened.

3.5.3. Technology is broadly acyclical

Technology, which is a blueprint to effectively use capital and labor, is likely to evolve even more smoothly than the capital stock. Think about a restaurant: it is clearly easier to buy an additional microwave oven than design new technology for the microwave. Technology is therefore something that we take as fixed over the business cycle.

Although it is difficult to say for sure, technology is likely acyclical. The invention process is slow and random. The diffusion process is slow and random. The depreciation process—the loss of know-how—is also slow and random. We can look at some proxies for technology to convince ourselves. The number of transistors per microprocessor grows steadily, without cyclical fluctuations (Rupp 2023). The same is true of the number of operations that can be carried out per second by the fastest existing supercomputers (Dongarra, Luszczek, and Petitet 2024).

It is true that technology is typically measured to be procyclical. But this is because technology is measured as a residual, whose fluctuations might be driven by slack (section 3.5.6).

3.5.4. Slack is sharply countercyclical

We saw previously that slack on the labor and product markets was countercyclical: higher in bad times than in good times. We now examine whether such fluctuations could possibly explain fluctuations in output—which are the most common marker of business cycles. We focus on the last 25 years of data, from 2000:Q1 to 2024:Q4, both because slack data are only fully available since 2000, and because the link between slack and output became tighter in the 21st century.

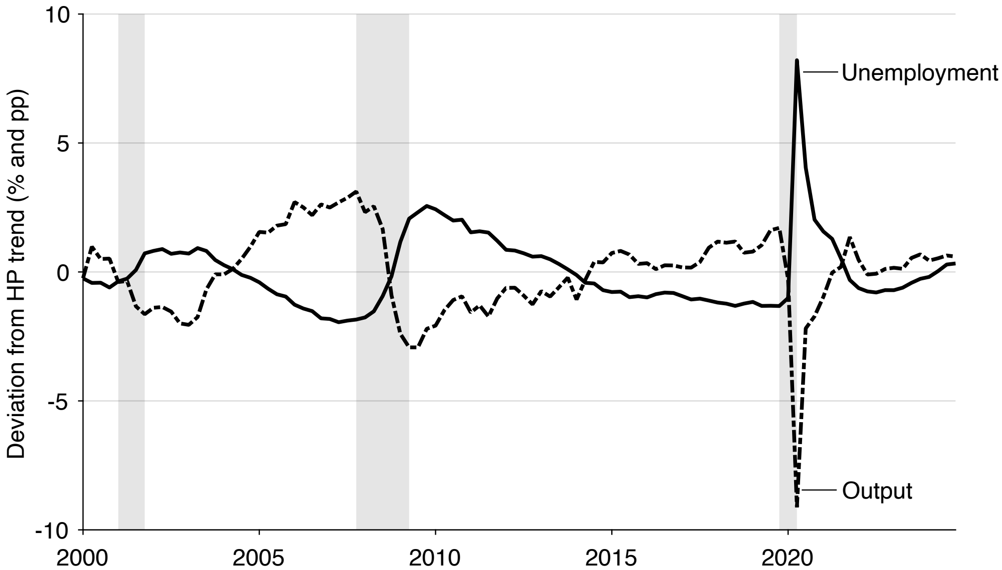
We first look at the connection between output and labor market slack. In figure 3.10A we superimpose cyclical fluctuations in output with those in unemployment. It appears that these fluctuations in unemployment could easily explain those in output since they are synchronized with them and of comparable amplitude. The correlation between the two series is almost −1, at −0.90.

In figure 3.10B we recast the results from figure 3.10A in the form of Okun (1963)'s law. Okun's law relates short-run movements in output and unemployment. In the United States, between 1948 and 2013, output and unemployment rate are negatively correlated in the short run: an increase in the unemployment rate by 1pp is associated with a reduction in output by about 2% (Ball, Leigh, and Loungani 2017). Between 2000 and 2024, the connection is instead one-for-one: a 1pp increase in unemployment is associated with a reduction in output by about 1%.

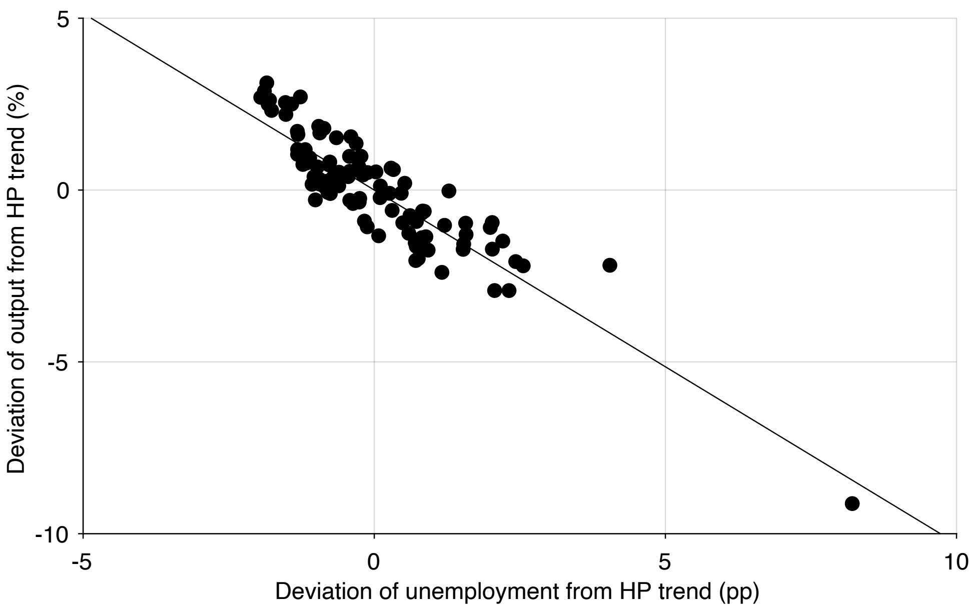
We also examine the connection between fluctuations in product market slack and output. Fluctuations in product market slack also contribute to fluctuations in output, but because these slack data are noisier, the connection is not as tight as in the case of unemployment.

Figure 3.11 correlates cyclical fluctuations in output with those in nonmanufacturing idleness. The fluctuations are quite negatively correlated, with a correlation coefficient of −0.72. So when there is more idle capacity in the nonmanufacturing sectors, output falls below trend. In Okun's law version with output and nonmanufacturing idleness, the slope is about 1/2: an increase in nonmanufacturing idleness by 1pp is associated with a reduction in output by roughly 0.5%.

The link between output and idleness is weaker in the case of manufacturing (fig-



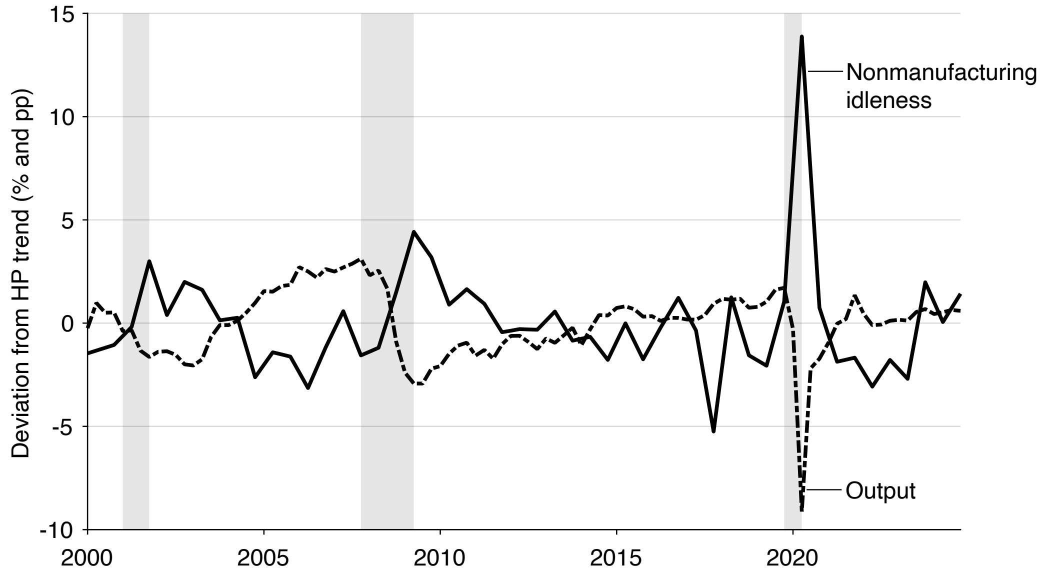
A. Correlation: −0.90



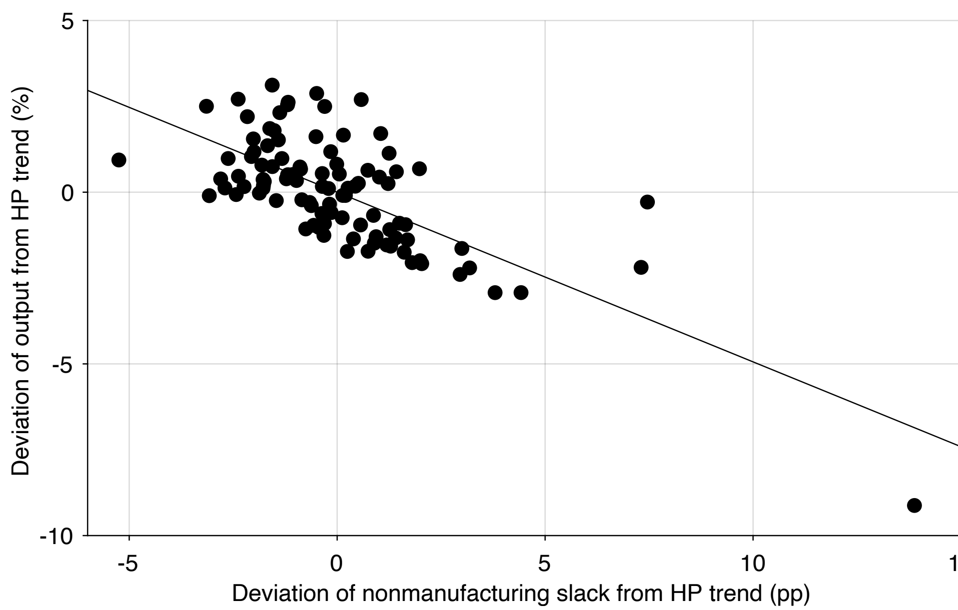
B. Estimated slope: −1.03

FIGURE 3.10. Okun's law with unemployment in the United States, 2000–2024

Detrended output comes from figure 3.9. Unemployment comes from figure 3.1. Unemployment is detrended by applying a HP filter with smoothing parameter of 10,000. Shaded areas indicate recessions dated by the NBER (2023).



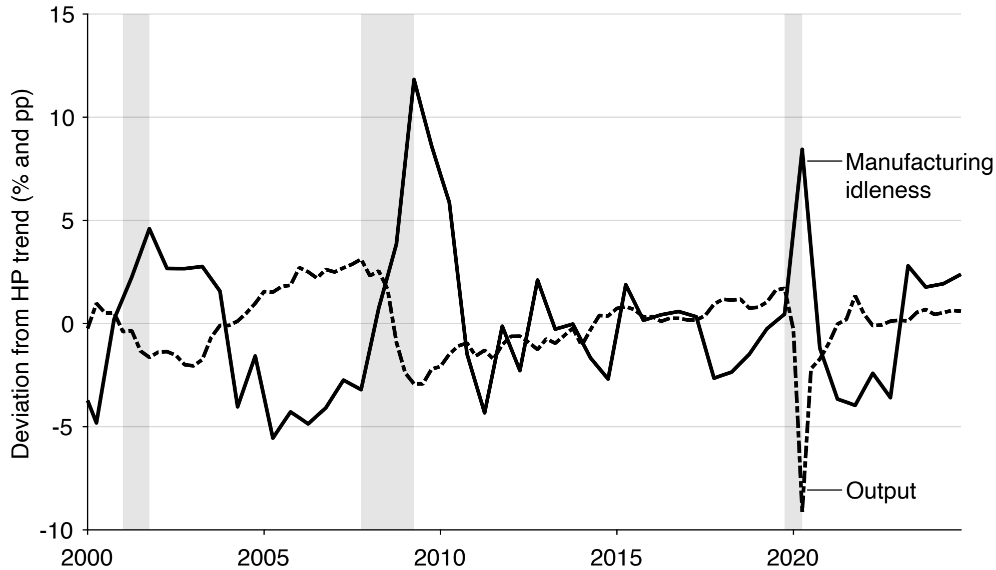
A. Correlation: −0.72



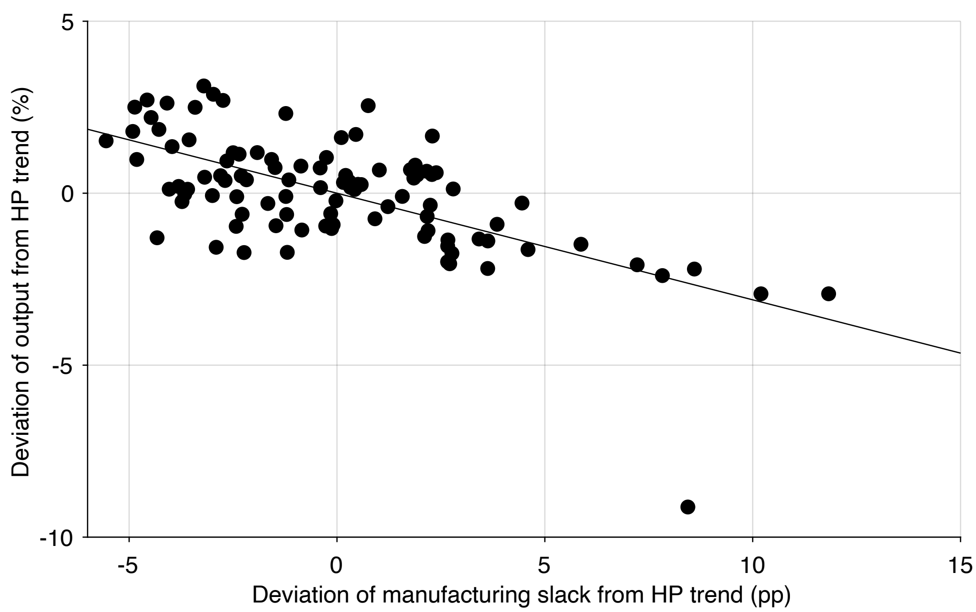
B. Estimated slope: −0.49

FIGURE 3.11. Okun's law with nonmanufacturing idleness in the United States, 2000–2024

Detrended output comes from figure 3.9. Nonmanufacturing idleness comes from figure 3.3. Idleness is detrended by applying a HP filter with smoothing parameter of 10,000. Shaded areas indicate recessions dated by the NBER (2023).



A. Correlation: −0.65



B. Estimated slope: −0.31

FIGURE 3.12. Okun's law with manufacturing idleness in the United States, 2000–2024

Detrended output comes from figure 3.9. Manufacturing idleness comes from figure 3.3. Idleness is detrended by applying a HP filter with smoothing parameter of 10,000. Shaded areas indicate recessions dated by the NBER (2023).

ure 3.12). Output does fall below trend when manufacturing idleness rises, but the correlation between the two series is only −0.65. This is not so surprising, given that manufacturing now only employs less than 10% of the US workforce, and produces less than 15% of US GDP (Baily and Bosworth 2014, figure 1). In an Okun's law version with output and manufacturing idleness, the slope is 1/3: an increase in the rate of manufacturing idleness by 1pp is associated with a reduction in output by about 0.3%.

3.5.5. Slack fluctuations are sufficient to account for output fluctuations

We have seen that in the US economy, a 1% change in output is associated with a 1pp change in unemployment rate (figure 3.10), a 2pp change in nonmanufacturing slack (figure 3.11), and a 3pp change in manufacturing slack (figure 3.12). We now show that these fluctuations in slack are more than sufficient to account for the fluctuations in output.

First, let's apply the slack identity (3.1) to the labor market. The slack identity becomes

$$\text{labor} = (1 - \text{labor market slack}) \times \text{labor force}. \tag{3.2}$$

The main component of labor market slack is unemployment. When the unemployment rate increases by 1pp, the term (1 – labor market slack) falls by roughly 1%, since the unemployment rate is small compared to 1. So if the labor force is fixed, the amount of labor drops by roughly 1%.

Next, we turn to the product market. The slack identity on the product market gives

$$\text{output} = (1 - \text{product market slack}) \times \text{capacity}(\text{technology}, \text{capital}, \text{labor}). \tag{3.3}$$

We use fluctuations in nonmanufacturing idleness as a measure of fluctuations in product market slack, since the nonmanufacturing sector is much larger than the manufacturing sector. We consider an increase in product market slack by 2pp, which again implies that the term (1 – product market slack) falls by roughly 2%. In addition, because labor falls by 1%, the productive capacity of firms, given by the production function, falls. Under the typical assumption that the aggregate production function takes a Cobb-Douglas form with an exponent 2/3 on labor, then firms' productive capacity falls by 2/3%. Combining the drop in productive capacity with the increase in product market slack, we conclude that output decreases by 2% + 2/3% = 2.7%, which is more than the output drop of 1% that we are targeting.

We conclude that the fluctuations in slack observed in the US economy can more than account for the fluctuations in US output, keeping all factors of production in the economy (labor force, capital stock, and technology) entirely fixed. Output fluctuations come from slack fluctuations on the labor market, through the mechanism described in (3.2), and from slack fluctuations on the product market, through the mechanism described in (3.3). In fact, we would expect even larger fluctuations in output given observed fluctuations in product market slack. A possible explanation is that the amount of idle capacity measured by the ISM (2025) is excessively volatile.

3.5.6. The illusion of procyclical technology

Furthermore, the framework suggests that measured procyclicality in technology, which is a cornerstone of modern business cycle models, may be an illusion created by unmeasured variations in slack. The evidence of the procyclicality of technology comes from measuring technology as a Solow residual. In the Solow procedure, output, capital, and labor are measured, but technology is inferred. The fluctuations in output that cannot be explained by fluctuations in capital and labor are assigned to fluctuations in technology, which is measured as a residual.

In our slackish model, however, there can be fluctuations in output even if capital and labor are fixed, because the rate of utilization of capital and labor varies over time, as shown in equation (3.3). Thus, fluctuations in technology, measured as a residual, could very well be fluctuations in slack. If we are in a world with slack and perform the Solow procedure to measure technology, variations in utilization will appear as variations in technology. The Solow procedure doesn't allow for fluctuations in utilization, so it might ascribe to technology what are fluctuations in slack. For instance, if restaurant workers are more idle in bad times, measured technology—the amount of meals sold per worker—will decrease, although the restaurant technology has not changed. Fewer meals are sold not because the ovens do not work as well but because fewer people eat out at restaurants. Interestingly, in US data, changes in capacity utilization mirror exactly changes in measured technology (Stock and Watson 1999, figures 3.31 and 3.32).

3.5.7. Lack of progress in stabilizing slack

Before we enter the main part of the book, it is important to recognize the scope for policy: despite major progress in other areas, very little progress has been made in stabilizing slack and unemployment.

Politicians and policymakers traditionally worry about three issues: output and its growth, inflation, and unemployment. The US economy has experienced a tremendous amount of growth in the last decades of the 19th century and during the 20th century. Over the entire period, per-capita output has grown at an average rate of around 2% per year Jones (2002, figure 1). With such growth and finite human needs, it seems that the amount of output available for consumption is sufficient in most places. Consumption is not distributed equally across people, of course, because income and wealth remain unequal in the United States.[5] Such inequality clearly remains a problem. But the total amount of consumption available seems sufficient.

Another common macroeconomic woe is inflation. The United States has struggled with inflation in the past: it was for instance a big issue in the 1970s. And people hate inflation.[6] Since the 1990s, however, US inflation has been stable around low levels. For more than a quarter century, between 1994 and 2020, core inflation remained between 0.7% and 2.6%, despite tumultuous events that included the boom and bust caused by the dot-com bubble and the Great Recession (BEA 2025a). By contrast, in the previous quarter century, between 1969 and 1993, core inflation varied between 2.5% and 10.1%. So the Federal Reserve has made tremendous progress in taming inflation. And such progress has undoubtedly been enabled by the insights from the New Keynesian literature. Obviously, US inflation has reached excessive levels in the aftermath of the coronavirus pandemic, but it subsided almost entirely within about 3 years. Time will tell if inflation returns more permanently.

Unlike other macroeconomic problems, little progress has been made about unemployment. The problem of unemployment manifests itself in several ways. First, over time, the average level of unemployment has not noticeably fallen (figure 3.1). Moreover, the peaks of unemployment continue to reach high levels. Of course, unemployment has never reached again the levels from the Great Depression—but the pandemic recession saw the highest peak in unemployment since 1940, and the Great Recession the third highest. Last, for certain socioeconomic groups, unemployment remains stubbornly high (Cairo and Cajner 2018, figure 1).

This lack of progress is undoubtedly due to the lack of slack in modern business cycle models: slack has been forgotten in the Real Business Cycle and New Keynesian models. That is why slack is the focus of this book. With a framework centered on slack, hopefully, policy will improve and fluctuations in unemployment and other forms of slack will subside, just like fluctuations in inflation have.

3.6. Social cost of slack

Finally, before building a theory of economic slack, we establish why having slack in a society is so problematic.

Slack matters in the first place because it represents a waste of productive resources. Labor that is available to produce value is left unused, which is something policy should try to limit or control. All goods, nondurable and durable, depreciate when they are not sold, which is socially costly. The most costly such form of slack is unsold food—both

[5] See for instance Piketty and Saez (2003), Saez and Zucman (2016), and Piketty, Saez, and Zucman (2018).
[6] See for instance Shiller (1997), Stantcheva (2024), and Georgarakos et al. (2025).

because food is the most necessary of goods, and because food perishes quickly. This is a mechanical cost of slack.

Additionally, one type of slack is particularly costly from a social perspective: unemployment. Beyond the waste of resources that unemployment imposes, it also generates significant psychological costs by keeping labor idle. That the idleness associated with unemployment creates psychological hardship goes against the idea that unemployed workers enjoy leisure time, but in reality such idleness does not seem enjoyable at all.

A final cost arises from the matching efforts exerted by households and firms in a slackish world. These efforts—such as recruiting on the labor market and purchasing on the product market—absorb time and labor which could otherwise be used to produce valuable goods and services.

3.6.1. Social cost of unemployment

In economics, we usually assume that there is a cost to working more. That cost is foregone leisure, and it explains why people do not work all the time. But while people out of the labor force (such as retired workers) may enjoy leisure time, unemployed workers, who are in the labor force, do not appear to enjoy their time without work. Being unemployed appears to be an extremely traumatic experience—among the worst events that can happen to an adult.

That is why, in addition to the wastefulness that it produces, unemployment generates large additional costs to society. People who are unemployed tend to suffer from lower mental health and lower physical health than people who are employed. Robinson (1949, p. 11) for instance observed that "The most striking aspect of unemployment is the suffering of the unemployed and their families—the loss of health and morale that follows loss of income and occupation." At this point, the detrimental effects of unemployment on psychological, physical, and public health have been well documented.[7]

Critically, unemployment carries substantial costs even when controlling for income and personal characteristics. In the US General Social Survey, Di Tella, MacCulloch, and Oswald (2003) find that the nonpecuniary cost from becoming unemployed can be as profound as the emotional distress experienced when going through a divorce or dropping from the top income quartile to the bottom. In the same survey, Blanchflower and Oswald (2004, p. 1373) confirm that the nonpecuniary toll of unemployment can be substantial, akin to the emotional impact of losing $60,000 in annual income. Using two large, daily US surveys, Helliwell and Huang (2014) confirm that for workers who have fallen into unemployment, the nonpecuniary costs are several times as large as the pecuniary costs. They also find that an increase in local unemployment reduces the well-being of workers

[7] See for example Dooley, Fielding, and Levi (1996), Platt and Hawton (2000), Frey and Stutzer (2002), McKee-Ryan et al. (2005), Wanberg (2012), Brand (2015).

who are still employed much more than what the reduction in local income would predict.

Where do the psychological costs of unemployment come from? The psychological costs associated with unemployment arise from various sources. First, depression, anxiety, and strained personal relations are common consequences of job loss (Eisenberg and Lazarfeld 1938). Job loss is a traumatic event that can lead to a decline in an individual's self-esteem and sense of self-worth (Goldsmith, Veum, and William Jr. 1996). Joblessness also diminishes psychological well-being by creating a sense of helplessness: that one's life is no longer under their control (Goldsmith and Darity 1992). Furthermore, job search appears to reduce unemployed workers' life satisfaction (Krueger and Mueller 2011).

In fact, Jahoda (1981) emphasizes numerous important benefits of work—which are lost during unemployment. A lot of people care about their job and derive a lot of meaning from their employment. Their personal status and identity come from their jobs. Other benefits from work encompass a structured daily routine, regular interactions and shared experiences and goals with individuals beyond the immediate family, and the engagement in regular activities. Collectively, the loss of these benefits contributes to the psychological burdens associated with unemployment.

As a final step, we assess the social product of unemployed labor. The value of job seekers' home production, net of the psychological cost of idleness, is estimated to be negligible. Using administrative data from the US military, Borgschulte and Martorell (2018) study how servicemembers choose between reenlisting and leaving the military. The choices allow them to estimate the value of home production plus public benefits minus the psychological cost of idleness during unemployment. Subtracting the value of public benefits from these estimates, Michaillat and Saez (2021, p. 11) find that the value of home production minus the psychological cost of idleness could be as low as 3% of the value of market production. Given its minimal value, we take the social product of unemployed labor to 0.

3.6.2. Social cost of recruiting

Employed workers must spend some of their time recruiting new hires for their firms, so they are unable to spend their entire time contributing to social output. Recruiting takes work: designing and advertising job vacancies, screening and interviewing candidates, and negotiating contracts.

Unfortunately, so far, there is only limited evidence on the number of recruiters in firms or the number of man-hours devoted to recruiting by firms. There are two sources of information about the amount of labor devoted to recruiting in the United States.

The first source of information about the amount of labor devoted to recruiting in the United States is from the National Employer Survey, which was conducted by the Census Bureau in 1997. The survey asked thousands of establishments across industries about their recruiting practices (Cappelli 2001; Villena Roldan 2010). On average, establishments report that they devote 3.2% of labor costs to recruiting, which implies that servicing a job vacancy requires 0.92 workers at any point in time (Michaillat and Saez 2021, p. 11).

A second source is the survey conducted by the consulting firm Bersin and Associates in 2011 (Gavazza, Mongey, and Violante 2018). The survey asked over 400 firms with more than 100 employees about their spending on all recruiting activities. Firms reported that recruiting one worker costs 93% of a monthly wage, which implies that it takes 1.16 workers to service a vacancy at any point in time (Michaillat and Saez 2024, p. 332).

Both surveys show that in the United States, it takes about 1 full-time worker to service a job vacancy. Thus, the number of vacancies is a good measure of the number of recruiters in the economy. So the number of workers diverted from producing and allocated to recruiting can be measured by the number of vacancies.

3.6.3. Social costs of product-market matching

A first social cost of matching arises from the vast amount of goods that are returned to retailers. We saw earlier that 10% of all retail sales, and 18% of online retail sales, are returned to sellers because the goods do not fulfill the needs of the buyers. These returns have substantial social costs, including extra shipping but especially the depreciation of the returned good. Indeed, returned goods can only rarely be sold as new; they are often sold at a discount or even discarded (Reagan 2019).

In addition, firms devote labor both to buying and selling goods and services. As such labor is diverted from producing goods and services, it is a source of social cost. In data recorded by the OES between 2003 and 2021, firms allocate 1.4% of employment to ordering, buying, purchasing, and procurement, and 1.9% of employment to advertising, marketing, sales, and promotion (Fernandez-Villaverde et al. 2025, p. 2508). Arkolakis (2010, Appendix A) reports that 4%–8% of US GDP is devoted to marketing, with advertising alone constituting 2%–3% of GDP.

3.7. Summary

In this chapter we saw that economic slack—the prevalence of unsold goods and services—is a pervasive feature of the US economy, not just a phenomenon of recessions. On the labor market, unemployment is always present, averaging about 6% since 1929 and spiking during recessions. On the product market, slack is even more prevalent. On average, firms operate with 14%–17% of capacity that is idle. Because slack is so prevalent, the Walrasian model is not well-suited to describe real-world markets.

An empirical puzzle is the coexistence of sellers and buyers who cannot find each other. In the labor market, this is captured by the Beveridge curve, which shows a negative relationship between unemployed workers and vacant jobs. It's because of this coexistence of vacant jobs and unemployed workers that we cannot use the nonclearing Walrasian model and must develop a new theory of slack. In the product market, we also always have buyers trying to purchase goods and services, together with goods and services for sale. This coexistence of buyers and sellers on markets points to a fundamental matching problem in the economy.

The chapter argues that business cycles correspond to fluctuations in slack, not in productive capacity. Inputs like capital stock, labor force, and technology are largely acyclical. In contrast, labor and product market slack is sharply countercyclical. Fluctuations in slack are more than sufficient to account for output fluctuations.

Finally, the chapter argues that slack is socially costly. First, it wastes productive resources: goods and services that could generate value remain unsold. Second, on the labor market, unemployment imposes severe nonpecuniary costs, because many people derive identity, status, and daily structure from work. Last, the presence of slack is associated with matching efforts that absorb resources which could otherwise be used to produce goods and services.

Bibliography

Aaronson, Stephanie, Tomaz Cajner, Bruce Fallick, Felix Galbis-Reig, Christopher Smith, and William Wascher. 2014. "Labor Force Participation: Recent Developments and Future Prospects." *Brookings Papers on Economic Activity* 45 (2): 197–275. `https://doi.org/10.1353/eca.2014.0015`.

Abraham, Katharine G. 1987. "Help-Wanted Advertising, Job Vacancies, and Unemployment." *Brookings Papers on Economic Activity* 18 (1): 207–248. `https://doi.org/10.2307/2534516`.

Anderson, Eric T., Gavan J. Fitzsimons, and Duncan Simester. 2006. "Measuring and Mitigating the Costs of Stockouts." *Management Science* 52 (11): 1751–1763. `https://doi.org/10.1287/mnsc.1060.0577`.

Arkolakis, Costas. 2010. "Market Penetration Costs and the New Consumers Margin in International Trade." *Journal of Political Economy* 118 (6): 1151–1199. `https://doi.org/10.1086/657949`.

Baily, Martin Neil and Barry P. Bosworth. 2014. "US Manufacturing: Understanding Its Past and Its Potential Future." *Journal of Economic Perspectives* 28 (1): 3–26. `https://doi.org/10.1257/jep.28.1.3`.

Ball, Laurence M., Daniel Leigh, and Prakash Loungani. 2017. "Okun's Law: Fit at 50?" *Journal of Money, Credit and Banking* 49 (7): 1413–1441. `https://doi.org/10.1111/jmcb.12420`.

Barnichon, Regis. 2010. "Building a Composite Help-Wanted Index." *Economics Letters* 109 (3): 175–178. `https://doi.org/10.1016/j.econlet.2010.08.029`.

BEA. 2025a. "Personal Consumption Expenditures Excluding Food and Energy (Chain-Type Price Index)." FRED, Federal Reserve Bank of St. Louis. `https://fred.stlouisfed.org/series/BPCCRO1Q156NBEA`.

BEA. 2025b. "Real Gross Domestic Product." FRED, Federal Reserve Bank of St. Louis. `https://fred.stlouisfed.org/series/GDPC1`.

BEA. 2025c. "Real Personal Consumption Expenditures (chain-type quantity index)." FRED, Federal Reserve Bank of St. Louis. `https://fred.stlouisfed.org/series/DPCERA3M086SBEA`.

Beveridge, William H. 1944. *Full Employment in a Free Society*. London: George Allen & Unwin.

Bils, Mark. 2016. "Deducing Markups from Stockout Behavior." *Research in Economics* 70 (2): 320–331. `https://doi.org/10.1016/j.rie.2016.03.001`.

Bils, Mark and James A. Kahn. 2000. "What Inventory Behavior Tells Us about Business Cycles."

American Economic Review 90 (3): 458–481. http://www.jstor.org/stable/117338.

Blanchard, Olivier J. and Peter Diamond. 1989. "The Beveridge Curve." *Brookings Papers on Economic Activity* 20 (1): 1–76. https://doi.org/10.2307/2534495.

Blanchflower, David G. and Andrew J. Oswald. 2004. "Well-Being Over Time in Britain and the USA." *Journal of Public Economics* 88 (7–8): 1359–1386. https://doi.org/10.1016/S0047-2727(02)00168-8.

Blinder, Alan S., Elie R. D. Canetti, David E. Lebow, and Jeremy B. Rudd. 1998. *Asking about Prices*. New York: Russell Sage Foundation.

BLS. 2023. "Labor Force Statistics from the Current Population Survey: Concepts and Definitions." https://perma.cc/6LGU-AEU6.

BLS. 2024. "JOLTS Frequently Asked Questions." https://perma.cc/22QW-ASAL.

BLS. 2025a. "Civilian Labor Force Level." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/CLF16OV.

BLS. 2025b. "Employment Level - Part-Time for Economic Reasons, Could Only Find Part-Time Work, All Industries." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/LNS12032196.

BLS. 2025c. "Employment Level - Part-Time for Economic Reasons, Slack Work or Business Conditions, All Industries." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/LNS12032195.

BLS. 2025d. "Job Openings: Total Nonfarm." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/JTSJOL.

BLS. 2025e. "Labor Force Participation Rate." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/CIVPART.

BLS. 2025f. "Labor Force Participation Rate - Men." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/LNS11300001.

BLS. 2025g. "Labor Force Participation Rate - Women." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/LNS11300002.

BLS. 2025h. "Population Level." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/CNP16OV.

BLS. 2025i. "Total Unemployed Plus Discouraged Workers, as a Percent of the Civilian Labor Force Plus Discouraged Workers (U-4)." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/U4RATE.

BLS. 2025j. "Total Unemployed, Plus Discouraged Workers, Plus All Other Persons Marginally Attached to the Labor Force, as a Percent of the Civilian Labor Force Plus All Persons Marginally Attached to the Labor Force (U-5)." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/U5RATE.

BLS. 2025k. "Unemployment Level." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/UNEMPLOY.

BLS. 2025l. "Unemployment Rate." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/UNRATE.

Borgschulte, Mark and Paco Martorell. 2018. "Paying to Avoid Recession: Using Reenlistment to Estimate the Cost of Unemployment." *American Economic Journal: Applied Economics* 10 (3): 101–127. https://doi.org/10.1257/app.20160257.

Brand, Jennie E. 2015. "The Far-Reaching Impact of Job Loss and Unemployment." *Annual Review of Sociology* 41: 359–375. https://doi.org/10.1146/annurev-soc-071913-043237.

Burns, Arthur F. and Wesley C. Mitchell. 1946. *Measuring Business Cycles*. New York: NBER.

Cairo, Isabel and Tomaz Cajner. 2018. "Human Capital And Unemployment Dynamics: Why More Educated Workers Enjoy Greater Employment Stability." *Economic Journal* 128 (609): 652–682. https://doi.org/10.1111/ecoj.12441.

Cairo, Isabel, Shigeru Fujita, and Camilo Morales-Jimenez. 2022. "The Cyclicality of Labor Force Participation Flows: The Role of Labor Supply Elasticities and Wage Rigidity." *Review of Economic Dynamics* 43: 197–216. https://doi.org/10.1016/j.red.2021.02.001.

Cappelli, Peter. 2001. "The National Employer Survey: Employer Data on Employment Practices." *Industrial Relations: A Journal of Economy and Society* 40 (4): 635–647. https://doi.org/10.1111/0019-8676.00230.

Cooley, Thomas F. and Edward C. Prescott. 1995. "Economic Growth and Business Cycles." In *Frontiers of Business Cycle Research*, edited by Thomas F. Cooley, chap. 1. Princeton, NJ: Princeton University Press.

Di Tella, Rafael, Robert J. MacCulloch, and Andrew J. Oswald. 2003. "The Macroeconomics of Happiness." *Review of Economics and Statistics* 85 (4): 809–827.

Dongarra, Jack, Piotr Luszczek, and Antoine Petitet. 2024. "Computational capacity of the fastest supercomputers." Our World in Data. https://ourworldindata.org/grapher/supercomputer-power-flops.

Dooley, David, Jonathan Fielding, and Lennart Levi. 1996. "Health and Unemployment." *Annual Review of Public Health* 17: 449–465. https://doi.org/10.1146/annurev.pu.17.050196.002313.

Dow, J. C. R. and L. A. Dicks-Mireaux. 1958. "The Excess Demand for Labour. A Study of Conditions in Great Britain, 1946–56." *Oxford Economic Papers* 10 (1): 1–33. https://doi.org/10.1093/oxfordjournals.oep.a040791.

Dube, Jean-Pierre, Gunter J. Hitsch, and Peter E. Rossi. 2010. "State Dependence and Alternative Explanations for Consumer Inertia." *RAND Journal of Economics* 41 (3): 417–445. https://doi.org/10.1111/j.1756-2171.2010.00106.x.

Eisenberg, P. and P. Lazarfeld. 1938. "The Psychological Effects of Unemployment." *Psychological Bulletin* 35 (6): 358–390.

Elsby, Michael W. L., Ryan Michaels, and David Ratner. 2015. "The Beveridge Curve: A Survey." *Journal of Economic Literature* 53 (3): 571–630. https://doi.org/10.1257/jel.53.3.571.

Erceg, Christopher J. and Andrew Levin. 2014. "Labor Force Participation and Monetary Policy in the Wake of the Great Recession." *Journal of Money Credit and Banking* 46 (S2): 3–49. https://doi.org/10.1111/jmcb.12151.

Fernandez-Villaverde, Jesus, Federico Mandelman, Yang Yu, and Francesco Zanetti. 2025. "Search Complementarities, Aggregate Fluctuations, and Fiscal Policy." *Review of Economic Studies* 92 (4): 2502–2536. https://doi.org/10.1093/restud/rdae053.

Frey, Bruno S. and Alois Stutzer. 2002. "What Can Economists Learn from Happiness Research?" *Journal of Economic Literature* 40 (2): 402–435. https://doi.org/10.1257/002205102320161320.

Gavazza, Alessandro, Simon Mongey, and Giovanni L. Violante. 2018. "Aggregate Recruiting

Intensity." *American Economic Review* 108 (8): 2088–2127. https://doi.org/10.1257/aer.20161420.

Georgarakos, Dimitris, Kwang Hwan Kim, Olivier Coibion, Myungkyu Shim, Myunghwan Andrew Lee, Yuriy Gorodnichenko, Geoff Kenny, Seowoo Han, and Michael Weber. 2025. "How Costly Are Business Cycle Volatility and Inflation? A Vox Populi Approach." NBER Working Paper 33476. https://doi.org/10.3386/w33476.

Goldberg, Pinelopi K. and Rebecca Hellerstein. 2011. "How Rigid Are Producer Prices?" Federal Reserve Bank of New York Staff Report 407. https://ideas.repec.org/p/fip/fednsr/407.html.

Goldsmith, Arthur H. and William Darity. 1992. "Social Psychology, Unemployment Exposure and Equilibrium Unemployment." *Journal of Economic Psychology* 13: 449–471. https://doi.org/10.1016/0167-4870(92)90004-Q.

Goldsmith, Arthur H., Jonathan R. Veum, and Darity William Jr. 1996. "The Impact of Labor Force History on Self-Esteem and its Component Parts, Anxiety, Alienation and Depression." *Journal of Economic Psychology* 17 (2): 183–220. https://doi.org/10.1016/0167-4870(96)00003-7.

Gourio, Francois and Leena Rudanko. 2014. "Customer Capital." *Review of Economic Studies* 81 (3): 1102–1136. https://doi.org/10.1093/restud/rdu007.

Hall, Robert E. 2012. "The Cyclical Response of Advertising Refutes Counter-Cyclical Profit Margins in Favor of Product-Market Frictions." NBER Working Paper 18370. https://doi.org/10.3386/w18370.

Helliwell, John F. and Haifang Huang. 2014. "New Measures of the Costs of Unemployment: Evidence from the Subjective Well-Being of 3.3 Million Americans." *Economic Inquiry* 52 (4): 1485–1502. https://doi.org/10.1111/ecin.12093.

ISM. 2025. "Semiannual Economic Forecast." https://perma.cc/A99Y-PY74.

Jahoda, Marie. 1981. "Work, Employment, and Unemployment: Values, Theories, and Approaches in Social Research." *American Psychologist* 36 (2): 184–191. https://doi.org/10.1037/0003-066X.36.2.184.

Janssen, Maarten and Cole Williams. 2024. "Consumer Search and Product Returns in E-Commerce." *American Economic Journal: Microeconomics* 16 (2): 387–419. https://doi.org/10.1257/mic.20230040.

Jing, Xiaoqing and Michael Lewis. 2011. "Stockouts in Online Retailing." *Journal of Marketing Research* 48 (2): 342–354. https://www.jstor.org/stable/23033435.

Jones, Charles I. 2002. "Sources of US Economic Growth in a World of Ideas." *American Economic Review* 92 (1): 220–239. https://doi.org/10.1257/000282802760015685.

Kalleberg, Arne L. 2001. "Evolving Employment Relations in the United States." In *Sourcebook of Labor Markets*, edited by Ivar Berg and Arne L. Kalleberg, chap. 8. Boston: Springer. https://doi.org/10.1007/978-1-4615-1225-7_8.

Katz, Lawrence F. and Alan B. Krueger. 2019. "The Rise and Nature of Alternative Work Arrangements in the United States, 1995–2015." *ILR Review* 72 (2): 382–416. https://doi.org/10.1177/0019793918820008.

Krueger, Alan B. 2017. "Where Have All the Workers Gone? An Inquiry into the Decline of the US Labor Force Participation Rate." *Brookings Papers on Economic Activity* 48 (2): 1–87. https:

//doi.org/10.1353/eca.2017.0012.
Krueger, Alan B. and Andreas Mueller. 2011. "Job Search, Emotional Well-Being and Job Finding in a Period of Mass Unemployment: Evidence from High-Frequency Longitudinal Data." *Brookings Papers on Economic Activity* 42 (1): 1–57. https://doi.org/10.1353/eca.2011.0001.
Kuhn, Thomas S. 1957. *The Copernican Revolution*. Cambridge, MA: Harvard University Press.
Macchiavello, Rocco. 2022. "Relational Contracts and Development." *Annual Review of Economics* 14: 337–362. https://doi.org/10.1146/annurev-economics-051420-110722.
McKee-Ryan, Frances, Zhaoli Song, Connie R. Wanberg, and Angelo J. Kinicki. 2005. "Psychological and Physical Well-Being During Unemployment: A Meta-Analytic Study." *Journal of Applied Psychology* 90 (1): 53–76. https://doi.org/10.1037/0021-9010.90.1.53.
Michaillat, Pascal and Emmanuel Saez. 2015. "Aggregate Demand, Idle Time, and Unemployment." *Quarterly Journal of Economics* 130 (2): 507–569. https://doi.org/10.1093/qje/qjv006.
Michaillat, Pascal and Emmanuel Saez. 2021. "Beveridgean Unemployment Gap." *Journal of Public Economics Plus* 2: 100009. https://doi.org/10.1016/j.pubecp.2021.100009.
Michaillat, Pascal and Emmanuel Saez. 2024. "$u^* = \sqrt{uv}$: The Full-Employment Rate of Unemployment in the United States." *Brookings Papers on Economic Activity* 55 (2): 323–390. https://doi.org/10.1353/eca.2024.a964373.
Monarch, Ryan and Tim Schmidt-Eisenlohr. 2023. "Longevity and the value of trade relationships." *Journal of International Economics* 145: 103842. https://doi.org/10.1016/j.jinteco.2023.103842.
NBER. 2023. "US Business Cycle Expansions and Contractions." https://perma.cc/B4LH-BVT8.
Okun, Arthur M. 1963. "Potential GNP: Its Measurement and Significance." Cowles Foundation Paper 190.
Petrosky-Nadeau, Nicolas, Etienne Wasmer, and Shutian Zeng. 2016. "Shopping Time." *Economics Letters* 143: 52–60. https://doi.org/10.1016/j.econlet.2016.02.003.
Petrosky-Nadeau, Nicolas and Lu Zhang. 2021. "Unemployment Crises." *Journal of Monetary Economics* 117: 335–353. http://doi.org/10.1016/j.jmoneco.2020.01.009.
Piketty, Thomas and Emmanuel Saez. 2003. "Income Inequality in the United States, 1913–1998." *Quarterly Journal of Economics* 118 (1): 1–41. https://doi.org/10.1162/00335530360535135.
Piketty, Thomas, Emmanuel Saez, and Gabriel Zucman. 2018. "Distributional National Accounts: Methods and Estimates for the United States." *Quarterly Journal of Economics* 133 (2): 553–609. https://doi.org/10.1093/qje/qjx043.
Platt, Stephen and Keith Hawton. 2000. "Suicidal Behaviour and the Labour Market." In *The International Handbook of Suicide and Attempted Suicide*, edited by Keith Hawton and Kees van Heeringen, chap. 20. Chichester, UK: John Wiley & Sons. https://doi.org/10.1002/9780470698976.ch20.
Reagan, Courtney. 2019. "That Sweater You Don't Like Is a Trillion-Dollar Problem for Retailers. These Companies Want to Fix It." CNBC. https://perma.cc/WZ2E-FSAM.
Rees, Albert. 1957. "The Meaning and Measurement of Full Employment." In *The Measurement and Behavior of Unemployment*, pp. 11–62. Cambridge, MA: National Bureau of Economic Research. http://www.nber.org/chapters/c2638.

ReFED. 2025. "From Surplus to Solutions." US Food Waste Report. https://perma.cc/3ZLP-QKHN.

Robinson, Joan. 1949. *The Problem of Full Employment*. London: The Workers' Educational Association & Workers' Educational Trade Union Committee, 2nd ed.

Rogerson, Richard and Robert Shimer. 2011. "Search in Macroeconomic Models of the Labor Market." In *Handbook of Labor Economics*, vol. 4A, edited by Orley C. Ashenfelter and David Card, chap. 7. Amsterdam: Elsevier. https://doi.org/10.1016/S0169-7218(11)00413-8.

Rupp, Karl. 2023. "Transistors per Microprocessor." Our World in Data. https://ourworldindata.org/grapher/transistors-per-microprocessor.

Saez, Emmanuel and Gabriel Zucman. 2016. "Wealth Inequality in the United States since 1913: Evidence from Capitalized Income Tax Data." *Quarterly Journal of Economics* 131 (2): 519–578. https://doi.org/10.1093/qje/qjw004.

Shiller, Robert J. 1997. "Why Do People Dislike Inflation?" In *Reducing Inflation: Motivation and Strategy*, edited by Christina D. Romer and David H. Romer, chap. 1. Chicago: University of Chicago Press. http://www.nber.org/chapters/c8881.

Shimer, Robert. 2009. "Convergence in Macroeconomics: The Labor Wedge." *American Economic Journal: Macroeconomics* 1 (1): 280–297. https://doi.org/10.1257/mac.1.1.280.

Stantcheva, Stefanie. 2024. "Why Do We Dislike Inflation?" *Brookings Papers on Economic Activity* 55 (1): 1–46. https://doi.org/10.1353/eca.2024.a943913.

Stock, James H. and Mark W. Watson. 1999. "Business Cycle Fluctuations in US Macroeconomic Time Series." In *Handbook of Macroeconomics*, vol. 1A, edited by John B. Taylor and Michael Woodford, pp. 3–64. Amsterdam: North-Holland. https://doi.org/10.1016/S1574-0048(99)01004-6.

Taylor, Johan C. and Stanley E. Fawcett. 2001. "Retail On-Shelf Performance of Advertised Items: An Assessment of Supply Chain Effectiveness at the Point of Purchase." *Journal of Business Logistics* 22 (1): 73–89. https://doi.org/10.1002/j.2158-1592.2001.tb00160.x.

University of Groningen and University of California–Davis. 2023. "Capital Stock at Constant National Prices for United States." FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/RKNANPUSA666NRUG.

Villena Roldan, Benjamin. 2010. "Aggregate Implications of Employer Search and Recruiting Selection." CEA Working Paper 271. https://perma.cc/Q3LE-C2AN.

Wanberg, Connie R. 2012. "The Individual Experience of Unemployment." *Annual Review of Psychology* 63: 369–396. https://doi.org/10.1146/annurev-psych-120710-100500.

Weir, David R. 1992. "A Century of US Unemployment : 1890–1990. Revised Estimates and Evidence for Stabilization." *Research in Economic History* 14: 301–346.

Zagorsky, Jay L. 1998. "Job Vacancies in the United States: 1923 to 1994." *Review of Economics and Statistics* 80 (2): 338–345. https://doi.org/10.1162/003465398557438.