# Slackish Business Cycles

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# CHAPTER 3.

# Social cost, prevalence, and cyclicality of slack

In this chapter we argue that economic slack—the underutilization of available resources—is not a rare phenomenon confined to deep recessions. It is a persistent and pervasive feature of modern economies, present in most markets at all times.

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 how costly slack might be, exactly how much slack there is out there, and how slack behaves over time. 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 amount of workers become unemployed. So, if we want to be able to understand these events, we must have a model that features some unemployment. What we will come to realize is 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 present on most markets at any point in time, in varying amounts. Therefore, a good macroeconomic model should feature slack in all markets, as well as fluctuations in slack.

## 3.1. Definition of economic slack

The concept of economic slack describes a situation in which goods or services are available for sale but the trade does not occur. When the goods or services are already produced, they have no marginal cost of production, so the trade would 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: a trade that would produce positive surplus for the seller and buyer does not materialize.

Of course, the concept of slack is completely antithetic to the Walrasian model. In a Walrasian model, it is assumed that 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. When there is slack, the 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 remain 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. Other examples would be 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 economic slack within firms. Slack affects job seekers on the labor market, but it also affects people who are employed within firms when firms do not have business. 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 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.

Of course, slack is not limited to blue-collar occupations. White-collar workers are not immune to it. In consulting firms, for instance, 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.

### 3.2. Social cost of slack

Before building a theory of economic slack, it seems important to 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.

Additionally, there is one specific type of slack that is particularly costly: unemployment. Studying unemployment is so important because unemployment is such an important social problem. Being unemployed is an extremely traumatic experience—among the worst events that can happen to an American adult. The most important reason why unemployment is such a big problem is that people care about their job. A lot of people derive a lot of meaning from life through their employment. Their identity comes from their jobs. If you deprive people of jobs, it is going to be very costly.

That is why, in addition to the wastefulness that it produces, unemployment generates large additional costs to society because 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 (Dooley, Fielding, and Levi 1996; Platt and Hawton 2000; Frey and Stutzer 2002; Wanberg 2012; Brand 2015).

It is not the case that what an unemployed person cannot produce is evenly spread out across everybody in society—the loss of income falls directly on the person who is unemployed. In addition, for a lot of people, their identity is tied to their occupation so when they lose their occupation, they lose their identity and that is very costly psychologically. This is why we care about unemployment and economic slack in general, because all of these things are interlinked.

Unemployment carries substantial costs, even when controlling for income and personal characteristics. Di Tella, MacCulloch, and Oswald (2003) highlight the psychological toll of economic recessions, which extends beyond the decline in output and the rise in unemployment figures. This importance of jobs can be seen by looking at well-being surveys, which are large scale surveys that ask respondents about their well-being. There are three factors that always come back as being important to people and unemployment is always among them. In the US General Social Survey, Di Tella, MacCulloch, and Oswald (2003) find that the emotional distress experienced when becoming unemployed can be as profound as going through a divorce or dropping from the top income quartile to the bottom. Other things that are very costly are divorce and losing a family member. This shows that having a job is very important to people. In similar surveys, Blanchflower and Oswald (2004) confirm that the psychological toll of unemployment can be substantial, akin to the emotional impact of losing $60,000 in annual income—three times the average yearly per-capita income.

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; Theodossiou 1998). 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. These benefits from work encompass a structured daily routine, regular interactions and shared experiences with individuals beyond the immediate family, the pursuit of overarching goals and purposes, a source of personal status and identity, and the engagement in regular activities. Collectively, the loss of these benefits contributes to the psychological burdens associated with unemployment.

A field experiment by Hussam et al. (2022) in Bangladesh illustrates just how large the psychosocial cost of unemployment is. The experiment shows that paid employment raises psychosocial well-being substantially more than the same amount of cash alone. In fact, two-thirds of the workers who were employed in the experiment would be willing to forgo cash payments and continue working for free.

### 3.3. 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.

### 3.3.1. Definition of unemployment

Before we look at the data, let us review how unemployment is defined and measured in the United States.

The definition of an unemployed worker 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 also 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. Note that foreigners who reside in the United States are included.

The working-age population is then divided into two categories. The larger category is the labor force—everyone who is either working or wants to be working. 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 not searching for one. These are people who are just not interested in working. There are several reasons why you could be out of the labor force: you could be retired, you could be studying full time, or you could be a stay-at-home parent.

The labor force, on the other hand, is people who either have a job or who are seeking employment. 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 two key criteria. First, you must not currently have a job, and second, you must want a job. The BLS gauges desire for a job by asking if you have been actively searching for a job in the past few 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 or recruiter, sitting for a job interview, submitting a resume or application, or using a placement agency. Formally, to be counted as unemployed one must have no job, be able and ready to work, and have been actively searching for a job in the past 4 weeks. People who have a job are counted as employed and people who have no job and are not actively searching for work are counted as out of the labor force.

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. If you do not have a job and do not want one (which is what people mean with "voluntary unemployment"), then you are not counted as unemployed: you are out of the labor force.

### 3.3.2. 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 the Bureau of Labor Statistics (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 State between January 1929 to December 2024. The shaded areas in the graph correspond to the official recession dates in the United States, which are officially identified by the Business Cycle Dating Committee of the National Bureau of Economic Research (NBER 2023). The NBER identifies these recessions by looking holistically at numerous macroeconomic variables. Between 1929 and 2024, the NBER identifies 15 recessions.

### 3.3.3. Prevalence of unemployed workers

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

First, the unemployment rate is countercyclical, rising sharply at the onset of all recessions. During the pandemic recession, the unemployment rate reached its highest level

[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.

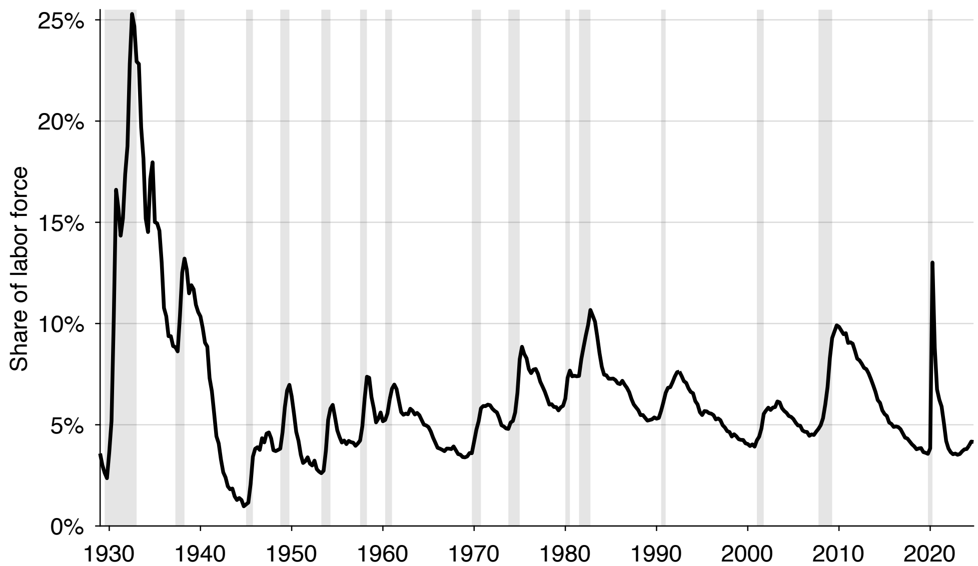



FIGURE 3.1. Unemployment rate in the United States, 1929–2024

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).

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 the Great Depression—even during the pandemic recession or Great Recession.

US recessions over the past century had entirely 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. But in all these recessions the unemployment rate spiked.

Although it is true that 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. Across all the major war episodes in the United States, 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. 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).

### 3.3.4. 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 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

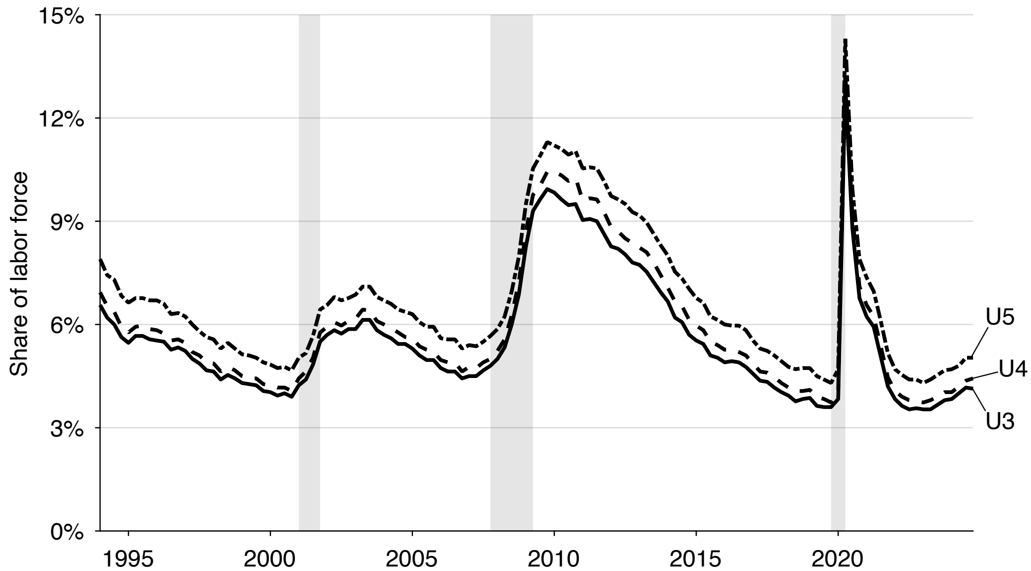



FIGURE 3.2. Alternative measures of unemployment in the United States, 1994–2024

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).

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 unemployment concepts U4 and U5 were only introduced in 1994, so we can only measure them since then (figure 3.2). The main takeaway is that the U4 and U5 rates are very close to the standard, U3 rate. Over 1994–2024, 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. By this I mean hours from workers who have a job that is only 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. Having a part-time job is much better than being unemployed; nevertheless, if a worker was willing to work full time but could only find a part time job, some of the hours that they were willing to supply are unemployed. Such workers are counted in the U6 concept of unemployment. But these workers are only a small sliver of the labor force. In 2024:Q4, the share of workers who were part time because they could not find a full-time job was only 0.7% of the labor force (BLS 2025b,a). And then only a fraction of the 35 hours that they could work was unemployed.

## 3.4. Prevalence of slack on the product market

We have seen that slack is prevalent on the labor market and takes the form of unemployed workers. But slack is not limited to the labor market; it is also prevalent on the product market. Just as not all workers who want to work can find a job on the labor market, producers are not able to sell all their goods and services to customers.

### 3.4.1. Prevalence of slack capacity

On the product market, slack is also prevalent. It takes the form of idle labor and capital. This is labor and capital that is available and ready to produce goods and services, but remain unused because of a lack of demand. It is a concept that is less common but still very prevalent.

There is not much systematic evidence on slack in the labor market, especially collected by government agencies, but fortunately we do have some data from the Institute for Supply Management (ISM 2025). The ISM keeps track of what they call 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 films could have achieved given their current capital and labor. From this operating rate, we can create a rate of slack, which is just one minus the operating rate. We can think of the slack rate as the amount of goods or services not sold as a fraction of the total capacity of a film given capital and labor, because of a lack of demand—it is the share of productive capacity that is idle.

In the United States, we find that there is some slack at all time (figure 3.3). The slack rate indicates the share of productive capacity, combining labor and capital, that is not sold due a lack of demand for the product. Between 1990 and 2024, the rate of slack in the manufacturing sector averages 17.3%. And between 2000 and 2024, the rate of slack 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 slack is the product-market equivalent of the rate of unemployment. Perhaps surprisingly, the rates of slack in the manufacturing and nonmanufacturing sectors are much higher than the rate of unemployment. There are several way to see this. The average rates of slack are higher than the average rate of unemployment rate between 1990 and 2024, which is only 5.7%. The manufacturing rate of slack is always above 10% and the nonmanufacturing rate of slack is always above 8%. Both lower bounds on slack 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 slack. The data thus show that more labor is idle within firms than outside them, making this internal slack a critical phenomenon.

Just like the rate of unemployment, the rates of slack are sharply countercyclical, climbing in recessions. Slack in the manufacturing sector peaked at 33.0%, during the Great Recession (2009:Q2). Manufacturing slack was also elevated during the other recessions in the data: the slack 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 recession (2020Q2). Slack in the nonmanufacturing sectors peaked at 26.7%, during the pandemic recession (2020:Q2). Nonmanufacturing slack also reached 19.9% after the Great Recession (2009:Q2) and 16.9% after the dot-com bubble recession (2001:Q4). Thus, it is evident that slack 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.

In addition to this evidence from the ISM, other evidence suggests that firms in the US face difficulties in selling their output. For instance, despite similar or lower prices, new production plants grow more slowly than similar plants with an established customer base because it is difficult for new plants to attract customers (Foster, Haltiwanger, and Syverson 2016).

Another manifestation is that firms spend substantial resources on sales and marketing: Firms spend substantial resources on marketing and selling. Using a variety of sources, Arkolakis (2010, Appendix A) reports that 4%–8% of US GDP is devoted to marketing, with advertising alone constituting 2%–3% of GDP. Based on a survey of 4,000 firms run by APQC, Fernandez-Villaverde et al. (2025) reports that 7.5% of firms' revenue is devoted to attracting customers. Moreover, 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 representative, and advertising agent (Gourio and Rudanko 2014). These resources are used by firms to increase their sales for a given productive capacity, and indicate that it not easy for firms to find customers, especially in slumps (Hall 2012).

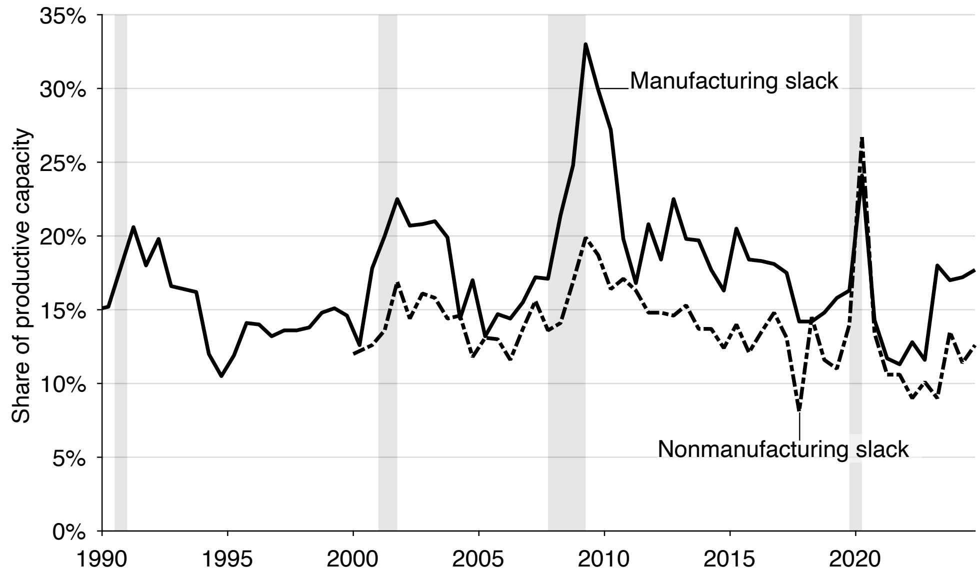



FIGURE 3.3. Slack rate in the United States, 1990–2024

The slack rate is a quarterly series constructed by interpolating the operating rate measured biannually by the Institute of Supply Management. For nonmanufacturing sectors, the operating rate is only available after 2000. Shaded areas indicate recessions dated by the NBER (2023).

### 3.4.2. Other forms of product market slack

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 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 of unfavorable business conditions or low seasonal demand. 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 their employers do not have sufficiently many customers.

Again, this is a form of product market slack, since the issue is that the workers' labor services cannot be sold to customers—not that workers cannot sell their labor to firms. These workers are actually included into the broadest unemployment concept U6 by the (BLS 2023), but it should not be interpreted as a measure of labor market slack: it is a measure of product market slack.

Between 1956 and 2024, we measure the share of these slack-induced part-time workers in the labor force (figure 3.4). We see first that there are a good number workers working part-time because of slack on the product market. On average 2.1% of the labor force is working less than full time because of product market slack; that share is always above 1%.

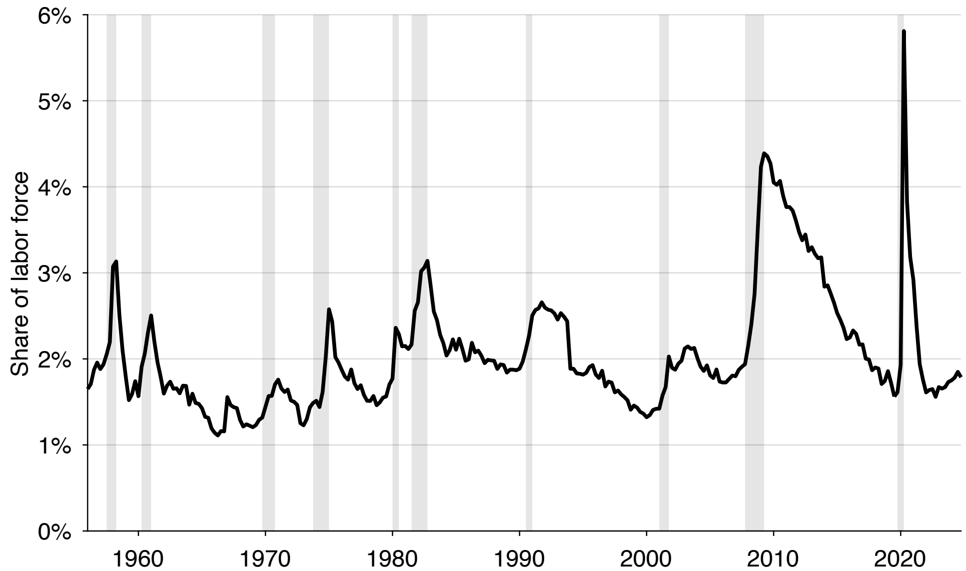



FIGURE 3.4. Workers forced to reduce hours because of product market slack in the United States, 1956–2024

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

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).

## 3.5. Coexistence of sellers and buyers

We have discussed slack on the labor market in the form of unemployed workers and slack on the product market in the form of idle labor. We could simply use a disequilibrium model—a Walrasian model with a non-market-clearing price—to explain these patterns. 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 disequilibrium 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 disequilibrium 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 recruiters and job vacancies has been well documented. We then turn to the product market, where the evidence is less readily available.

### 3.5.1. Coexistence of job seekers and recruiters on the labor market

On the labor market, not only do we always have unemployed workers trying to find jobs, but we also always have employed workers trying to recruit labor. This is something that the disequilibrium model cannot explain, since it suggests that we can either have unemployed workers and no vacant jobs, or have vacant jobs and no unemployed workers—we cannot have both. But what we see is that actually, there are always jobs that are vacant at the same time that there are workers that are unemployed. It's because of this coexistence of vacant jobs and unemployed workers that we cannot use the disequilibrium model and must develop a new framework of slack that features both vacant jobs and unemployed workers on the labor market.

The presence of recruiters in firms, or workers devoting time to recruiting, is the concrete manifestation that firms are looking to hire labor—just like workers devoting time to active job search or hiring head hunters to help them find jobs is the concrete manifestation that a worker is looking to find a job.

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, which provide US recruiting costs at one point in time, but not in a time series. The first source sources 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 (Michaillat and Saez 2021). A second source is the survey conducted by consulting firm Bersin and Associates in 2011. 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 (Gavazza, Mongey, and Violante 2018).

How can we assess whether firms wants to hire workers at any point in time without knowing how much labor they devote to recruiting. 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 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 a vacancy rates.

Next, we splice the three vacancy series to create a continuous vacancy rate covering

[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 April 2025 the number of job openings that the BLS assigns to March 2025. 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 31 March 2025), while the labor force from the CPS refers to the Sunday–Saturday week including the 12th of the month (Sunday 6 April 2025–Saturday 12 April 2025). 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.

[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.

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 exists 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 followed the Great Depressions: 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.

### 3.5.2. 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 situation are 2003:Q2, when the unemployment rate was 6.2% and the vacancy rate 2.2%, and 2009:Q4, when the unemployment rate was 9.9% and the vacancy rate 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 was only 3.8% and the vacancy rate reaches 4.3%.

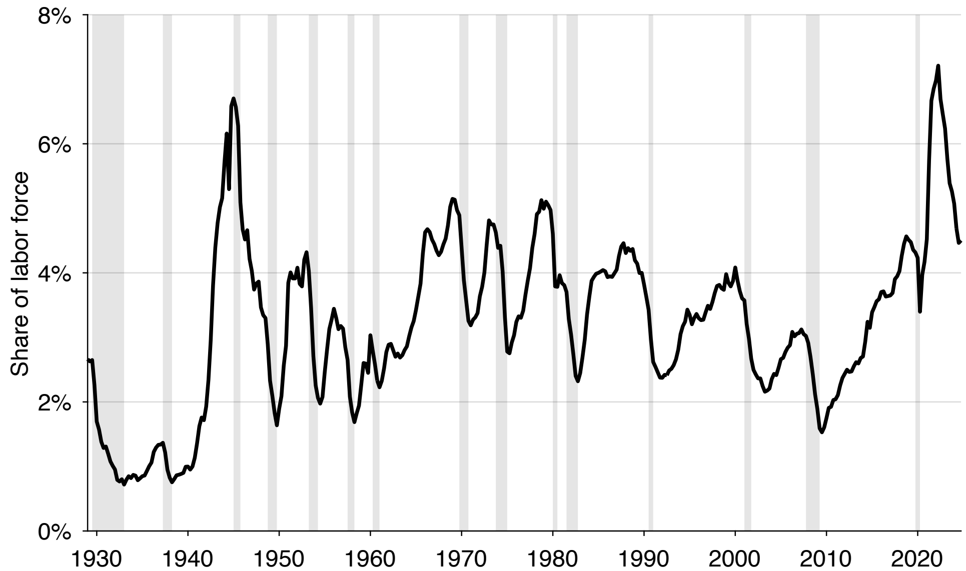



FIGURE 3.5. Vacancy rate in the United States, 1929–2024

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).

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 most noisy 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 16—because they generate jumps in the full-employment rate of unemployment (FERU).

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

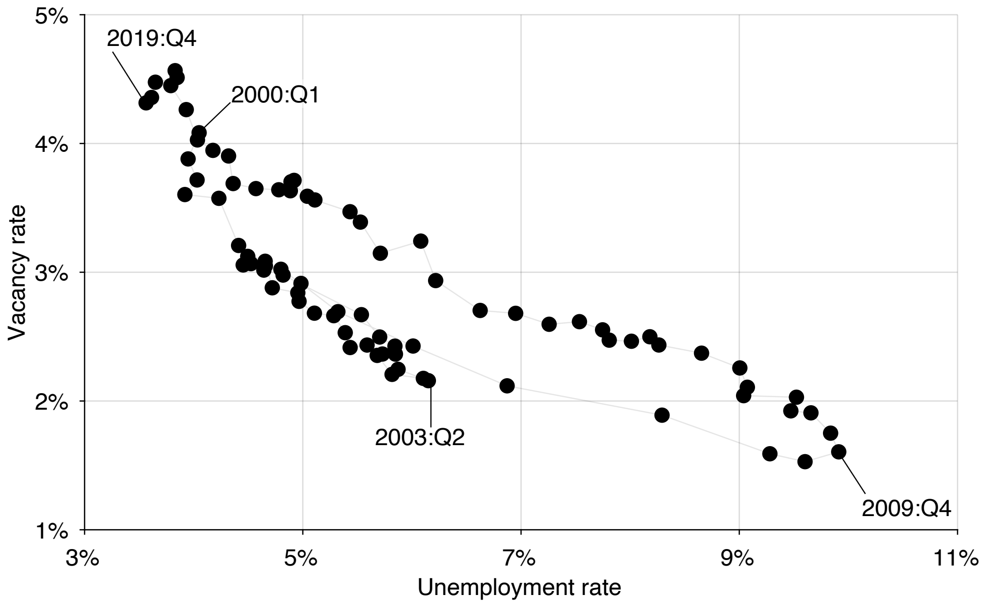



FIGURE 3.6. Beveridge curve in the United States in recent decades, 2000–2019

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

is always tightly on the Beveridge curve.

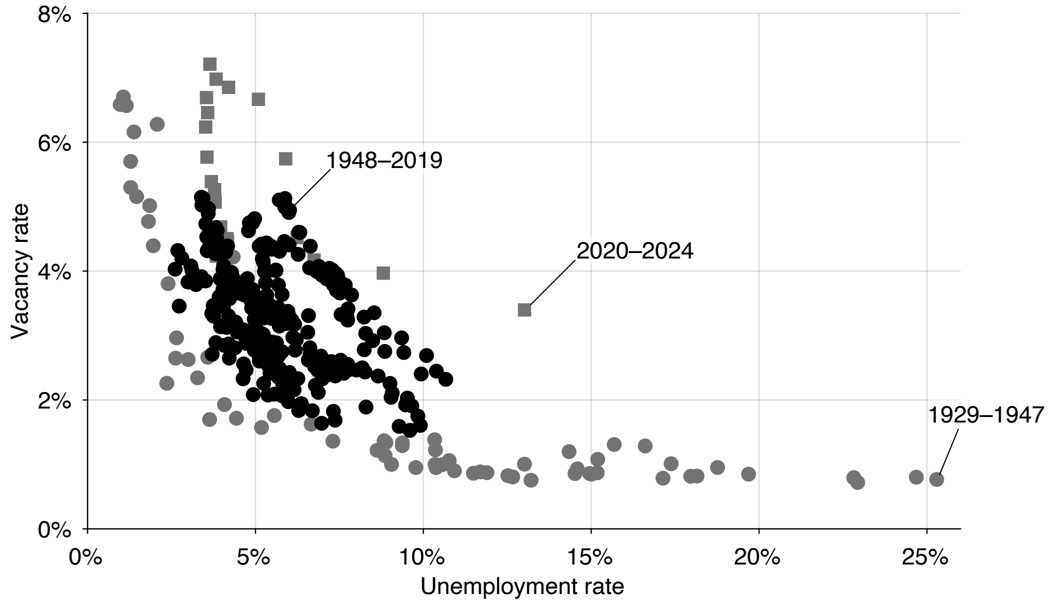
Finally, the last subperiod corresponds to the coronavirus pandemic and its aftermath, 2020–2024. The pandemic shattered the US labor market and dramatically shifted the Beveridge curve outward. The Beveridge curve slowly recovered from the pandemic shift over the next few years and it only came back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

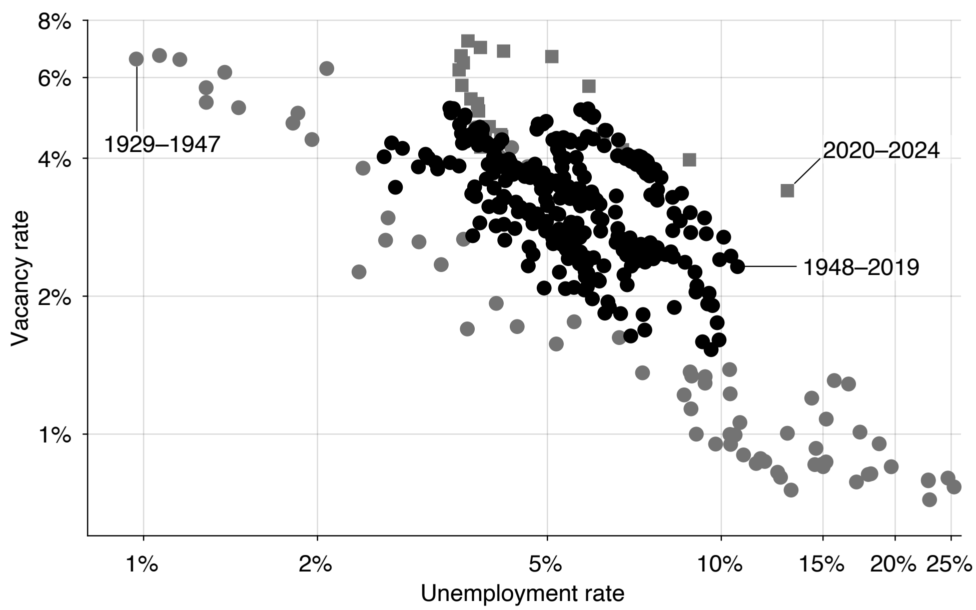
$$v u = \beta, \tag{3.1}$$

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




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 come from figure 3.5.

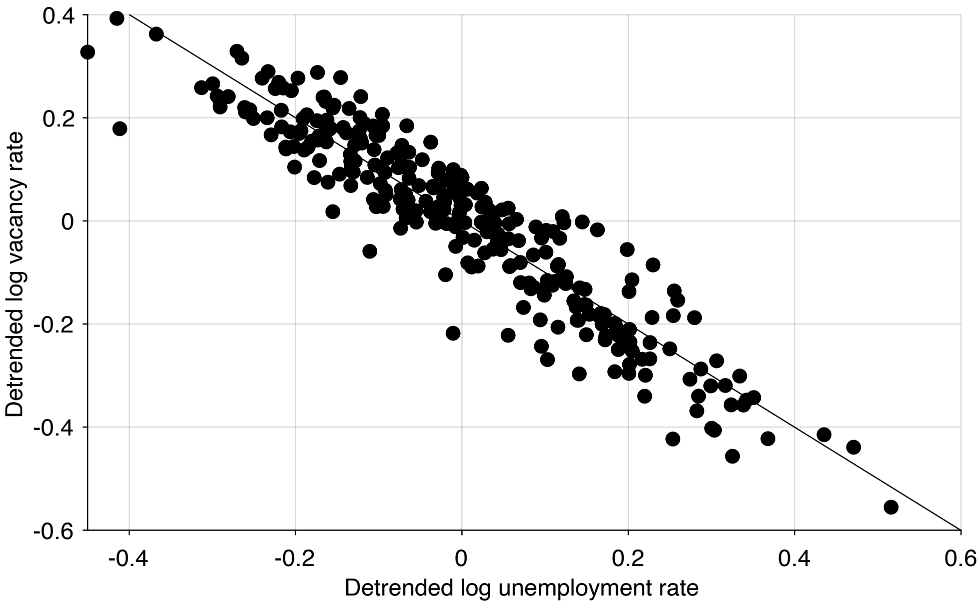



FIGURE 3.8. US Beveridge curve approximates a rectangular hyperbola

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

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 an 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 by HP filter with smoothing parameter 10,000. We do the same to the log vacancy rate. We then 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 a seventy-year period, 1948–2019.

### 3.5.3. Coexistence of buyers and sellers on the product market

On the product market, we also see that we always have buyers trying to purchase goods and services, together with goods and services for sale, and some sellers trying to sell these items. Again, this is something that the disequilibrium model cannot explain: in that model with there is excess supply with sellers and no buyers, or there is excess demand with buyers but no sellers.

For instance, firms devote labor both to buying and selling goods and services at any point in time. 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).

Time-use data recorded by the BLS through the American Time Use Survey (ATUS) show that US consumers spent a significant amount of time shopping, driving to shops, researching their shopping, and waiting in line at shops. 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).

One reason why buying takes time, and at some times more than at other times, is that goods are not always available in shops. A stockout is an item not available for sale, continuing to be carried by the outlet, and not seasonally unavailable; hence, a stockout indicates that a buyer's visit to a store would not result in a purchase because the desired product would be unavailable. 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. 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. In data from an online retailer, Jing and Lewis (2011, table 1) find that 25.4% of orders were imperfectly filled—in the sense that some of the items that were ordered could not be shipped to the customer. The monetary value of the items in stockout represents 9.7% of the total value of the orders.

It also appears that stockouts are quite costly to sellers. The cost goes well beyond the foregone sale, as customers are generally upset by the fact that they drove to a shop, where they expected to find the product, and were not able to find it (Taylor and Fawcett 2001). In a field experiment conducted in a mail-order catalog, Anderson, Fitzsimons, and Simester (2006) confirm that stockouts not only eliminate the profits earned on the out-of-stock item, but also reduce profits on other items in the order. Moreover, they find that stockouts damage long-run profits: when customers experience a stockout, they significantly reduce their long-run demand for the catalog's products.

We saw that the amount of slack on the product market is at least as large as slack on the labor market (figure 3.1 versus figure 3.3). Similarly, the amount of labor devoted by firms to source goods and services might not be very different from the amount of labor 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). Of course these numbers underestimate the total amount of labor devoted to buying or recruiting in the US economy since there are many workers whose occupation is not buying or recruiting but who devote a significant amount of time on buying or recruiting. But the data suggests that buying is a significant activity on both the product market and the labor market.

### 3.6. Prevalence of long-term relationships

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 both on the labor market and on the product market.

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% percent 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 contractor (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), but it seems that the number of workers in alternative work arrangements increased by a few percentage points between the 1990s and 2010s, 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. 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 addition, a sizable share of transactions on the product market are conducted under explicit contracts that link sellers and buyers over time. Using 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.”

Long-term customer relationships are governed by implicit contracts that alleviate matching frictions, as I found in a survey of French bakers in the summer of 2007 (the survey is described in Eyster, Madarasz, and Michaillat 2021). First, I found that customer relationships alleviate the uncertainty associated with random demand. A baker told me that demand is difficult to predict and that having a large clientele of loyal customers who make it a habit to purchase bread in the shop was therefore important. In fact, “good” customers are expected to come everyday to the bakery. I also saw that customer relationships alleviate the uncertainty associated with random supply. Being a customer means having the assurance that your usual bread will be available, even on days when supply runs low. Of course, this is possible because bakers know exactly what customers order every day through their long association. In fact, one baker said that it would be “unacceptable” to run out of bread for a customer, and that customers would probably “leave the bakery” if that happened.

### 3.7. Business cycle accounting in the 21st century

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.

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 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 production identity: production = productive capacity × utilization. Since slack = 1 − utilization by definition, we can rewrite the production identity as follows:

$$\text{(3.2)} \qquad \text{production} = \text{productive capacity} \times [1 - \text{slack}]$$

Equation (3.2) shows that there are two possible and nonexclusive sources of business-cycle 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: share of the working-age civilian population that wishes to work and is available. Third is technology: the blueprint to the production process, and the effectiveness of capital and labor. All 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.

### 3.7.1. Introduction to the HP filter

Several of the variables that we examine now, and in the book, grow exponentially over time. To isolate cyclical fluctuations of these variables, it is necessary to first remove their trends. To do that, we use the Hodrick-Prescott (HP) filter. We pick the HP filter because it is convenient to use, and it is standard in business cycle research.[4]

The HP filter takes a time series $y(t)$ and extracts a trend $\tau(t)$ from it, so that the initial series can be decomposed as $y(t) = \tau(t) + \delta(t)$, where $\tau(t)$ moves smoothly over time and $\delta(t)$ is the deviation of the series from trend, or in the context of business cycles, the cyclical fluctuations of the series. In practice, the HP filter requires that the deviation from trend, or cycle, $\delta(t)$ is stationary process (which requires that $\delta(t)$ has a constant mean and variance). So the filter can be applied directly to a series that is not growing (such as the unemployment rate). But if the series grow exponentially (such as consumption or output), then applying the HP filter directly produces cycles whose variance grows with the level of the series. That means that $\delta(t)$ is not stationary, and the decomposition no longer has the properties the HP filter is built for. Hence, the HP filter must be applied to the logarithm of a series if it is growing exponentially. Logging the series enforces that its cycle is stationary.

Before using the HP filter, we must specify a smoothing parameter $\lambda$, which determines how smooth the trend extracted by the filter is. If $\lambda = 0$, the trend is just the series ($y(t) = \tau(t)$). When $\lambda \to \infty$, the trend is linear ($\tau(t) = g \cdot t$). In between, the trend evolves smoothly over time. Ravn and Uhlig (2002) recommend a smoothing parameter of 1,600

[4]The HP filter was introduced in modern macroeconomics by Hodrick and Prescott (1997), but it was discovered by mathematician Whittaker (1923), and popularized among actuaries by Henderson (1924). The Whittaker-Henderson smoothing method was well-known to macroeconomists in the 1930s (Macaulay 1931, chapter 6).

with quarterly data; this is the standard value in business cycle research. However, as Shimer (2012, p. 132) notes in the context of US labor market data, setting $\lambda = 1,600$ “seems to remove much of the cyclical volatility in the variable of interest.” To keep more cyclicality, Shimer (2005, 2012) set $\lambda = 100,000$ instead. Here, we want to keep fluctuations of interest but also apply the same filter both to labor market data and to other business cycle data. So we pick an intermediate point between 1,600 and 100,000: we set the smoothing parameter to $\lambda = 10,000$. We use that parameter throughout the book, whenever detrending is required.

### 3.7.2. Capital is broadly acyclical

Because we want to have a model that represents the real world well, we must question how much the capital stock varies 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, in our model, we will assume that the capital stock is constant.

### 3.7.3. Labor force is broadly acyclical

We must also think about how much labor supply varies 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 subject to medium run fluctuations. 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). These are the medium-run forces that are driving this result; it clearly doesn't have much to do with the business cycle.

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 business cycle models) 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 massive drop in participation by 3pp, from 63% to 60%, which was something we had never seen before. Of course, this was because it became dangerous to work, and people had new childcare obligations due to school closures, so workers decided to drop out of the labor force. The participation rate recovered once working became safe again and school reopened.

### 3.7.4. Technology is broadly acyclical

Technology, which is a blueprint for the effectiveness of capital and labor, must grow even slower than capital stock does. This makes sense if we think about a restaurant as an example: it is clearly easier to buy an additional microwave oven than design new technology for the microwave. Technology is therefore something that we will take as fixed over the business cycle.

Although it is difficult to measure, technology is likely acyclical. In practice, technology is bound to be divorced from business cycles. Invention process is slow and random. The diffusion process is slow and random. The depreciation process (loss of know-how) is also slow and random. We can look at some proxies for technology to convince ourselves. For instance, 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 supercomputers in the world (Dongarra, Luszczek, and Petitet 2024).

It is true that total factor productivity (TFP) is typically found to be procyclical. But TFP is measured as a residual, and its fluctuations seem to be driven almost exclusively by factor utilization (section 3.7.6).

### 3.7.5. Slack is sharply countercyclical

In contrast to capacity, slack is sharply countercylical. Slack on the labor market appears as follows:

$$\text{employment} = (1 - \text{unemployment}) \times \text{labor force} \tag{3.3}$$

Slack on the product market with production function $f$ appears as follows:

$$\text{output} = (1 - \text{idleness}) \times f(\text{technology, capital, employment}) \tag{3.4}$$

There are therefore two forms of slack in the economy. One form is unemployment: the share of the labor force that is not employed. The other is idleness: the share of firms' productive capacity that is not in use.

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 GPD and consumption is 0.92.

This 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 book will abstract from imports and exports as we will work with closed-economy models. It will also abstract investment as we will not model capital goods. While one might worry that a model abstracting from investment and trade could not explain output fluctuations, figure 3.9 shows that private consumption moves so closely with output that our focus is well-suited to the task.

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.

In figure 3.10A we superimpose cyclical fluctuations in output with those in unem-

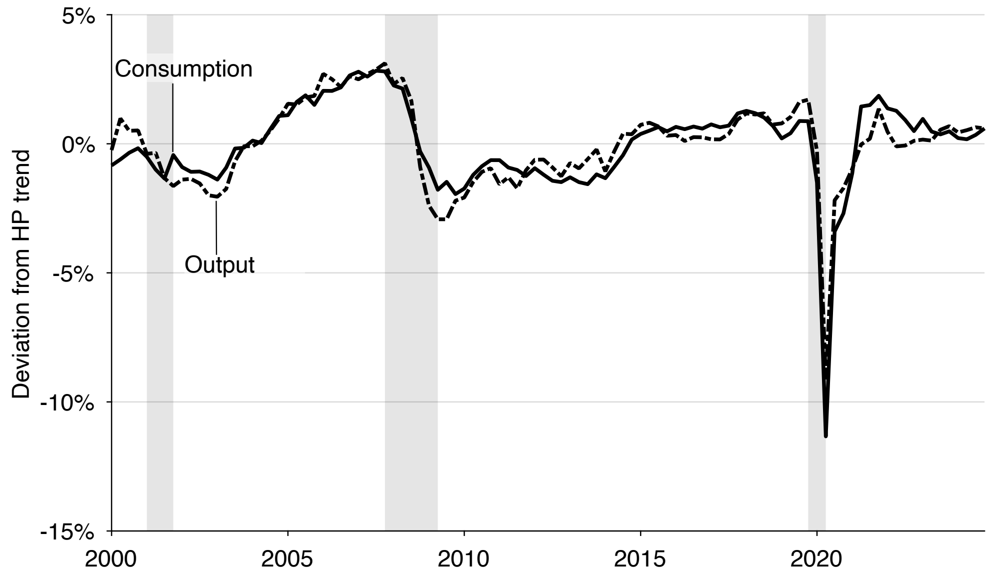



FIGURE 3.9. Business cycle fluctuations in consumption and output in the United States, 2000–2024

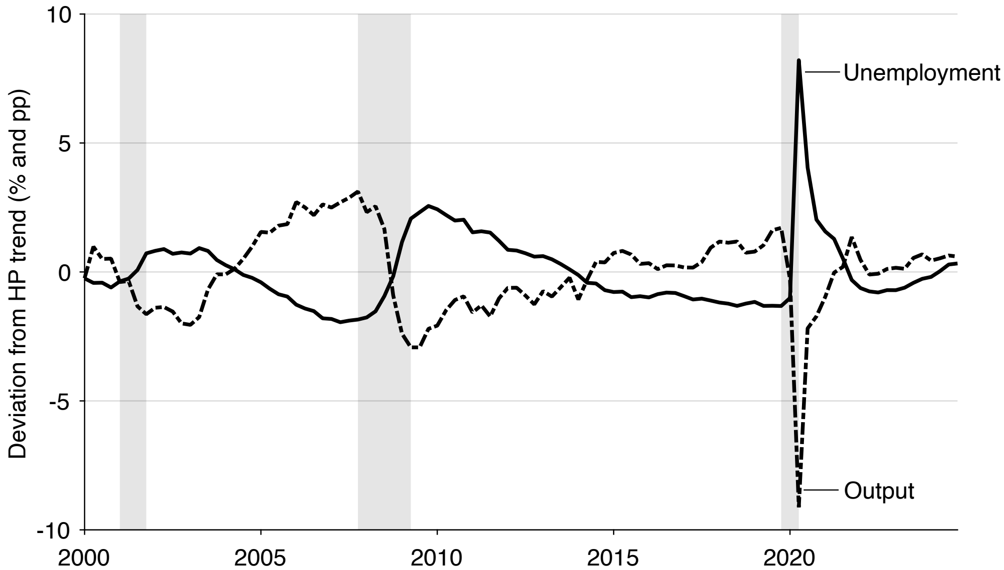
Output is real gross domestic product measured by the BEA (2025b). Consumption is real personal consumption expenditure measured by the BEA (2025c). The original series are quarterly and seasonally adjusted. The series are detrended by applying a HP filter to their logarithms with smoothing parameter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

ployment. 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.

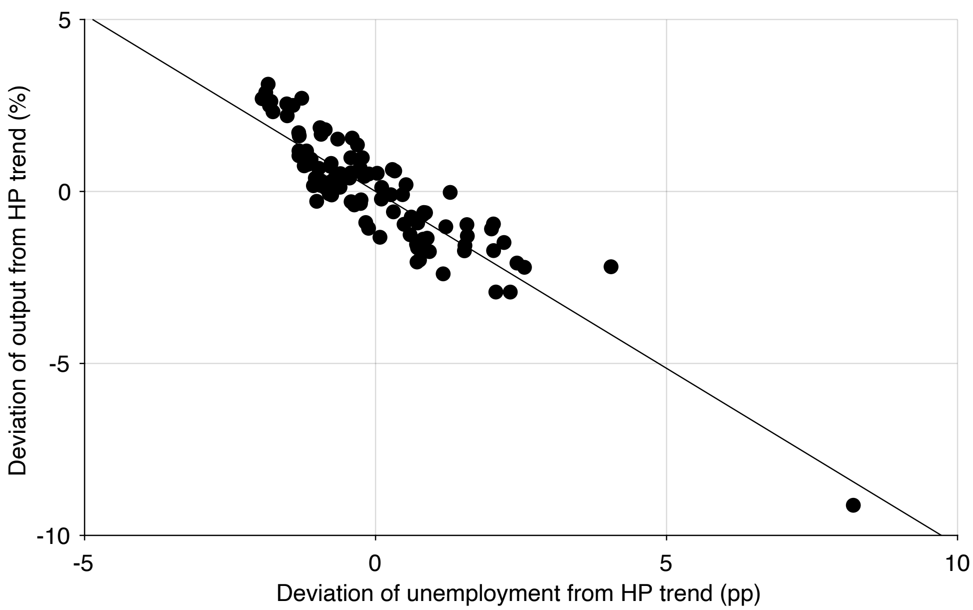
In figure 3.10B we recast the results from figure 3.10A in the form of Okun (1963)'s law. Okun's law relates short-run movements in output and unemployment. In the United States, between 1948 and 2013, output and unemployment rate are negatively correlated in the short run: an increase in the unemployment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

We also examine the connection between fluctuations in product-market slack and output. Fluctuations in product-market slack might 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 slack. The fluctuations are quite negatively correlated, with a correlation coefficient of −0.72. So when there is more slack in the nonmanufacturing sectors, output tend to fall below trend. In Okun's law version with output and nonmanufacturing slack, the slope is half of what is was in the output-unemployment version: an increase in the rate of



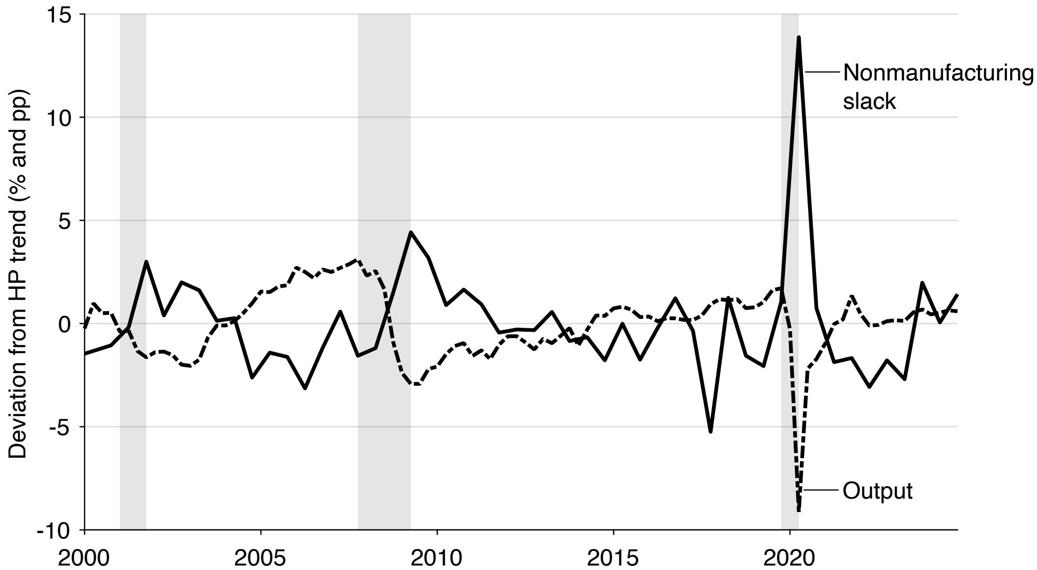

A. Correlation: −0.90



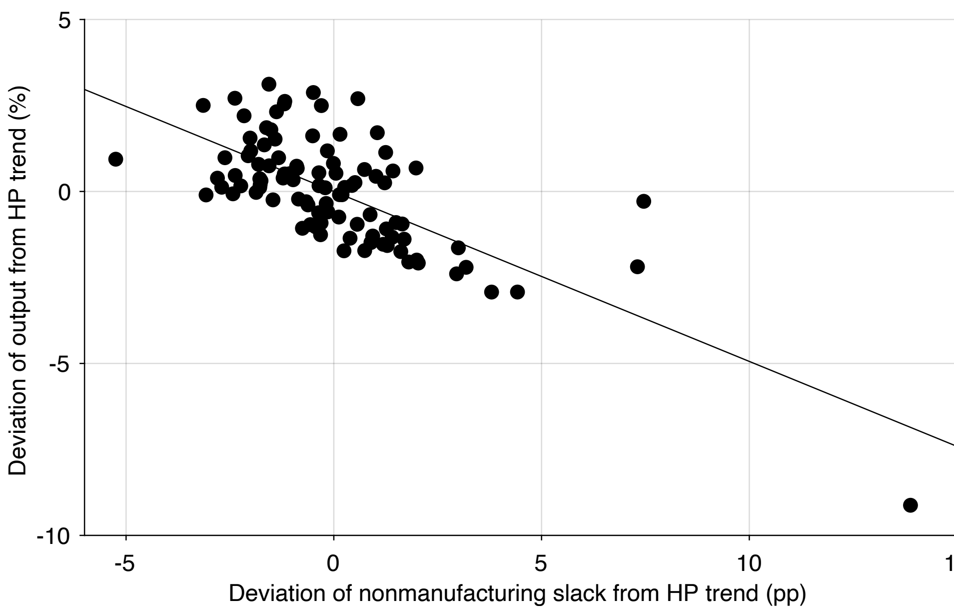

B. Estimated slope: −1.03

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.




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 slack comes from figure 3.3. Slack is detrended by applying a HP filter with smoothing parameter of 10,000.

nonmanufacturing slack by 1pp only reduces output by roughly 0.5%.

The link between output and slack is weaker in the case of manufacturing slack (figure 3.12). Output does fall below trend when manufacturing slack rises, but the correlation between the two series is only −0.31. 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 slack, the slope is one-third of what is was in the output-unemployment version: an increase in the rate of nonmanufacturing slack by 1pp only reduces output by about 0.3%.

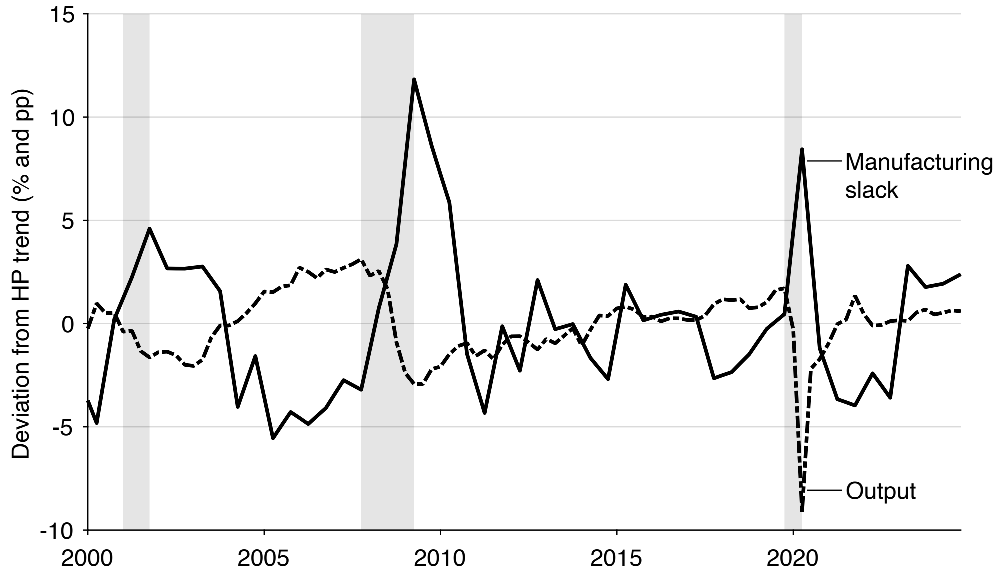
Nevertheless, the overall conclusion is that fluctuations in slack are more than sufficient to explain fluctuations in output mechanically, through equations (3.3) and (3.4).

### 3.7.6. The illusion of procyclical technology

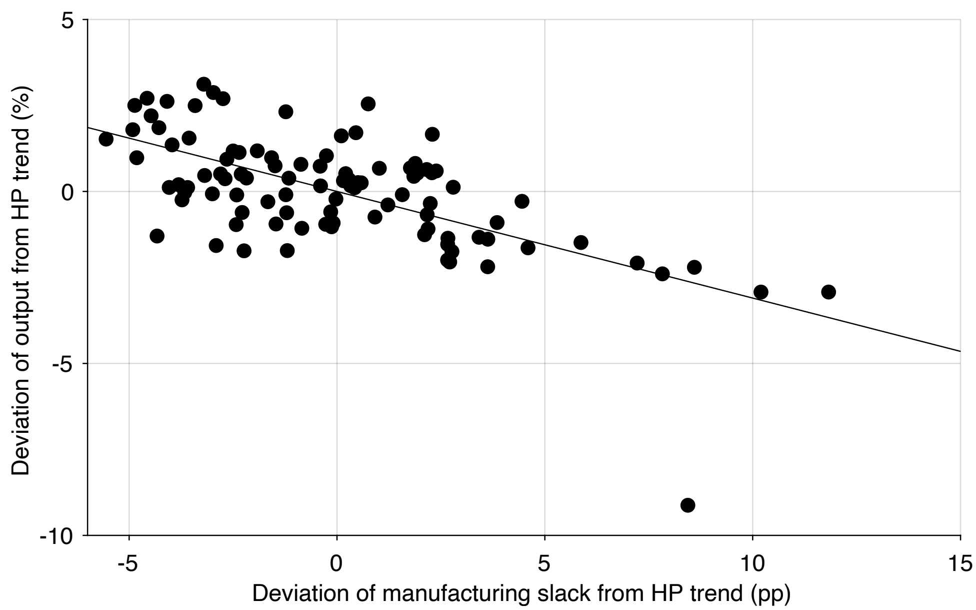
Furthermore, the framework suggests that measured procyclicality in technology, which is a cornerstone of modern business-cycle models, may be an illusion created by unmeasured variations in slack. The evidence of the procyclicality of technology comes from measuring technology as a Solow residual. In the Solow procedure, we assume that output = technology × $f(\text{capital}, \text{labor})$. Output is measured, as well as capital and labor in the production function, but technology is inferred. The fluctuations in output that cannot be explained by fluctuations in capital and labor are assigned to fluctuations in technology—this is measured as a residual.

In our slackish model, however, there can be fluctuations in output even if capital and labor are fixed, because of rate of utilization of capital and labor varies over time, as showed in equation (3.4). Thus, fluctuations in technology, measured as a residual, could very well be just fluctuations in slack.

If we really are in a world with slack, and carry out the Solow procedure to measure technology, then variations in utilization are going to look like variations in measured technology. In fact, this would be inaccurate because the Solow procedure doesn't allow for fluctuations in utilization, so it ascribes to technology what are really fluctuations in slack. Of course, if workers are more idle in bad times, then measured technology—the amount of services produced by given worker—can decrease just because there are less consumers in bad times even though the actual underlying technology is exactly the same. With the Solow procedure, it may look like technology varies, but it may not be variations in technology at all and instead variations in slack. Indeed, in the data, changes in capacity utilization mirror exactly changes in measured technology (Stock and Watson 1999, figures 3.31 and 3.32).




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 slack comes from figure 3.3. Slack is detrended by applying a HP filter with smoothing parameter of 10,000.

### 3.8. Lack of progress in stabilizing slack

Before we enter the main part of the book, it's important to realize the scope there is for policy: slack is the one problem on which modern macroeconomic policy has not made any progress.

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 (Piketty and Saez 2003; Saez and Zucman 2016; Piketty, Saez, and Zucman 2018). Such inequality clearly remains a problem. But the total amount of consumption available seems sufficient. Thus, output and output growth should not be a real concern any more in the United States.

Another common macroeconomic woe is inflation. It is true that the United States has struggled with inflation in the past: it was for instance a big issue in the 1970s. It is also true that people hate inflation (Shiller 1997; Stantcheva 2024). Since the 1990s, however, inflation has been stable around low levels in the United States. For instance, 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 there is no doubt that a huge amount of progress has been achieved in conducting monetary policy and taming inflation. And central banking has made a lot of progress undoubtedly thanks to 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.

In contrast to growth and inflation, unemployment remains an unsolved problem. Unlike other macroeconomic problems, little progress has been made about unemployment. The US economy continues to experience sharp fluctuations in unemployment, and for certain socioeconomic groups, unemployment remain stubbornly high (Cairo and Cajner 2018, figure 1).

The problem of unemployment manifests itself in several ways. If you look at the amount of unemployment since we have had statistics, you see that unemployment remains on average at the same level (figure 3.1). We have not made systematic progress in improving unemployment, the fluctuations of unemployment remain quite high. Of course, unemployment has never reached again the levels from the Great Depression—but that's a low bar. The pandemic recession saw the highest peak in unemployment on record since 1940, and the Great Recession the third highest.

This lack of progress is undoubtedly due to the lack of slack or unemployment in modern business-cycle models. Both the Real Business Cycle and the New Keynesian models have no slack whatsoever. In the New Keynesian model markets are not efficient, but they have no slack. Therefore, slack and unemployment have been forgotten. That is why they are the focus of this book. With a framework centered on slack, hopefully, policy will improve and fluctuations in unemployment and slack will subside, just like fluctuations in inflation have.

## 3.9. Summary

In this chapter we saw that economic slack—the prevalence of unsold goods and services—is a persistent and pervasive feature of modern economies, not just a phenomenon of recessions. Slack is present in most markets at all times and represents a significant social cost, most notably through the psychological trauma and wasted potential of unemployment.

The evidence shows slack is widespread. On the labor market, unemployment is always present, averaging 6.4% in the United States since 1929 and spiking during every recession. On the product market, slack is even more prevalent. US firms operate with an average of 14%–17% idle capacity, meaning they could sell significantly more with their existing labor and capital if demand were higher. The presence of slack is a complete repudiation of the Walrasian market model.

A key 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 stable, negative relationship between unemployed workers and vacant jobs. This coexistence refutes disequilibrium market models as an explanation of slack and points to a fundamental matching problem in the economy.

Finally, the chapter argues that business cycles are driven primarily by fluctuations in slack, not by changes in productive capacity. Core inputs like capital stock, the labor force, and technology are largely acyclical and grow smoothly over time. In contrast, measures of slack such as unemployment and capacity utilization are sharply countercyclical and their movements are sufficient to explain the fluctuations we observe in GDP. This suggests that the procyclicality of measured technology—a key source of business cycles in modern macroeconomic models—is likely an illusion created by unmeasured variations in slack.

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