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Digitalization: Implications for Monetary Policy

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Overview

While the economic impacts of digitalization are clearly visible across many segments of the economy, its implications for monetary policy are more complex, and the related literature is in its infancy. This paper assesses the implications of digitalization for monetary policy, both in terms of its direct effect on central banks' inflation-targeting objectives and in terms of central bank communications and data analysis. Other papers in this Digitalization Overview series explore the impacts of digitalization on prices, employment and productivity. In this paper, we connect the insights from those papers to monetary policy. We do this through the lens of a simple New Keynesian model (section 1). To this effect, we consider how digitalization might affect the structural parameters of the New Keynesian Phillips curve (NKPC) à la Galí (2008). We then explore the consequences for the two key endogenous variables in the NKPC—the output gap (via potential output) and expected inflation. Another dimension of digitalization's effect on monetary policy is how it is changing the data available to central banks (section 2). This can lead to better communication as well as a timelier and sharper picture of the economy. Beyond data, we also contemplate the impacts of new techniques needed to make this progress feasible. We conclude by looking ahead and raising key questions (section 3).

Key messages

- **Digitalization has the potential to increase or dampen the responsiveness of inflation to monetary policy through its impact on the slope of the NKPC**. The overall net impact will depend on which of several offsetting channels dominate in practice. The nascent empirical research on this question remains inconclusive.
- **Digital technologies have not had a large impact on central banks' communications with the public.** While social media present opportunities for central banks to communicate directly with the public and have been used increasingly in recent years, online discussion by the public can also lead to misinformation.
- **Digitalization has increased the availability of (often unstructured) data**. The advantages of these data relative to conventional sources include broader coverage, increased frequency and timeliness, and finer granularity. Yet disadvantages also exist, as these data tend to be less-curated, not seasonally adjusted and often harder to work with.
- **By expanding the techniques to collect and manipulate these data, digitalization has made it possible for central banks to draw economic insights from this information.** These techniques allow practitioners to extract information from previously unused types of data (e.g., text, sound, images). At the same time, machine learning is increasingly being used in monitoring and forecasting applications. But the lack of transparency of these methods limits their usefulness for monetary policy.

1. Digitalization and the transmission mechanism of monetary policy

To systematically discuss the impacts of digitalization on the transmission mechanism of monetary policy, we use the NKPC, a central equation of the New Keynesian model relevant to central bank policy. In its basic form, the NKPC relates consumer price inflation to both the degree of economic slack (summarized by the output gap) and expected future inflation. The relationships are governed by several parameters related to the overall structure of the economy, which are, in turn, influenced by digitalization. Monetary policy impacts inflation primarily by influencing economic slack and inflation expectations.

We begin by outlining the economic relationships underlying the NKPC. The NKPC is the mathematical formulation describing how price inflation today responds to the output gap, household and firm expectations of future inflation, and changes to firms' desired markups. We then discuss the likely implications of digitalization for the key structural parameters that determine the strength of these relationships, drawing from to the insights of the other papers in this Digitalization Overview series. The specific parameters of interest largely determine:

- the slope of the NKPC—that is, the strength of the transmission of monetary policy to inflation via its impact on economic slack
- the intercept term, which in this context captures the direct effect of markups on inflation, among other factors

1.1 Structural parameters of the New Keynesian Phillips curve

Several key implications of digitalization for monetary policy transmission relate directly to the effects on firms' price-setting behaviour, on productivity and labour market dynamics, and on market competition (reviewed in the other papers in this Digitalization Overview series). To summarize these relationships in a succinct and intuitive way, we rely on a slightly augmented version of the NKPC presented in Galí (2008):

$$\pi_t = \gamma(d_t) + \beta E_t\{\pi_{t+1}\} + \kappa(y_t - y_t^n). \tag{1}$$

In this framework, which is described in more detail in **Box 1**, π_t represents current-period inflation and $E_t\{\pi_{t+1}\}$ is expected inflation in the next period. The term $(y_t - y_t^n)$ is the output gap—the difference between aggregate output y_t (expressed in natural logarithms) and the natural rate of output, y_t^n. Each of these variables is determined endogenously. The structural parameters are β (representing the rate at which future consumption and returns are discounted, and lying between 0 and 1), κ is the slope term (which is strictly positive), and $\gamma(d_t)$ is the intercept. The intercept captures the temporary direct dependence of inflation on changes in firms' desired markup, which we express as a function of digitalization intensity, d_t. We refer to this relationship as the markup channel. In this section, we discuss how digitalization is expected to affect the key structural parameters of the model—the slope and intercept. We then turn to implications for potential output and expected inflation.

Slope channel

The slope (κ) captures the sensitivity of inflation to changes in economic slack. It also reflects the potency of monetary policy transmission—that is, the response of inflation to a given monetary stimulus that raises aggregate demand $y_{t.}$ In the simplest version of the model, the slope is expressed as the following function of the structural parameters:

$$\kappa = \left(\frac{(1-\theta)(1-\theta\beta)}{\theta + \theta\epsilon\left(\frac{\alpha}{1-\alpha}\right)}\right)\left(\sigma + \frac{\eta + 1 - \alpha}{\alpha}\right) > 0. \tag{2}$$

The interpretation of each of the key parameters (θ, α and ϵ) is clarified below. For a more complete discussion of parameter definitions and model intuition, see the Appendix.

Box 1 provides an overview of the New Keynesian framework and economic interpretation of the NKPC relationship and discusses the various ways in which key model parameters could evolve in response to structural changes brought by digitalization. The likely effect of digitalization on the slope of the NKPC depends on which of the following channels dominates:

- **Degree of price stickiness** (θ)—As discussed in Chu, Dahlhaus and Hajzler (forthcoming), digital technologies and the proliferation of e-commerce tend to increase price flexibility, since online prices appear to change more frequently than offline prices. This steepens the slope of the Phillips curve, which translates into more-volatile inflation in response to changes in aggregate demand or supply.
- **Labour share** ($1 - \alpha$)—To the extent that digitalization is contributing to the rise in superstar firms, the labour share in aggregate income is likely to decrease.[1] This view is supported by the empirical evidence reviewed in section 4 of Chu, Dahlhaus and Hajzler (forthcoming). This would flatten the slope and lead to less-volatile inflation.
- **Price elasticity of demand** (ϵ)—Digitalization has been found to lead to greater product variety (e.g., Brynjolfsson, Hu and Smith 2003). This would tend to increase the elasticity of demand, flattening the Phillips curve.

Which of these potentially opposing effects dominates is an empirical question. For example, the NKPC would become steeper and inflation more volatile if the impact of e-commerce on the flexibility of price setting and product varieties is more dominant than the potentially negative impact on the labour share.

The extent of research that empirically models the impacts of digitalization on the NKPC relationships is new and still limited. This research is particularly challenging, not only

[1] *Superstar firms* are companies that achieve monopoly scale through large investments in (typically intangible) assets, such as research and development and branding. As discussed in Chernoff and Galassi (2023), digitalization can increase or decrease the share of labour in aggregate income. The evidence considered in section 4 of that paper suggests that digitalization has tended to decrease the labour share by contributing to the rise in monopolistic power in some industries and to the increased substitutability between capital and labour. Nevertheless, depending on a country's skill composition, digitalization could increase the labour share through factor-biased technological change (i.e., if digitalization is biased toward a type of skilled labour), steepening the NKPC. The relationship between digitalization and the rise of superstar firms is also discussed in more detail in Chu, Dahlhaus and Hajzler (forthcoming), section 4.

because of the difficulties in measuring digitalization but also because it requires exploiting cross-sectional variation based on (possibly limited) country data.[2] Results that depend on cross-country variation in the data should be interpreted cautiously given the likely dissimilarities in national monetary policies, Phillips curve relationships and industrial compositions.

Taken together, the findings are rather inconclusive. For example, Csonto, Huang and Tovar (2019) proxy digitalization with the number of nationwide IP addresses, which they use to construct an interaction term with a measure of economic slack (the deviation of unemployment from trend) in a panel regression model of the NKPC. To address the usual data challenges discussed above, they select a digitalization measure that is available at a monthly frequency for a large sample of advanced and emerging economies.[3] The interaction term aims to capture the marginal impact of digitalization on the NKPC slope, but they do not find a statistically significant effect. In contrast, using a measure of industrial robot adoption as a proxy for digitalization, Friedrich and Selcuk (2022) find that greater digitalization intensity is associated with larger slope estimates across a set of industry-specific Phillips curves.[4] This would be consistent with the notion that robot technology reduces menu costs or enables firms to optimize prices more frequently and accurately.

The divergence in findings across these two studies may be attributed to the different digitalization proxies, which could be impacting the slope more strongly through one of the distinct opposing channels discussed above. However, the many data challenges and the highly different approaches make it difficult to compare their findings. More research is needed to understand how different aspects of digitalization impact the responsiveness of inflation to economic slack and monetary policy.

Markup channel

If digitalization has an effect on the optimal firm markup, inflation can be temporarily impacted as firms increase or decrease their markups to the new desired levels.[5] In principle, the impact

[2] The low (typically annual) frequency of most measures of digitalization combined with the fact that widespread adoption of many digital technologies is relatively recent make it difficult to identify these relationships based on time-series variation alone.

[3] The rationale for this measure is that IP addresses are required for digital connectedness, including e-commerce, digital communications and remote data transfer (enabling working from home). Using monthly data for 31 countries from 1990 to 2017 provides a panel of over 9,000 country-month observations. This allows the authors to exploit much more variation in the data than is possible when restricted to annual observations.

[4] Data on robot intensity are from the International Federation of Robots, as discussed in Faucher and Houle (forthcoming). To overcome the limited cross-country and time-series variation in annual robot adoption, Friedrich and Selcuk (2022) proceed in two steps. First, they estimate industry- and country-specific Phillips curves for 18 advanced economies and 31 industries, using the deviation in industry employment from trend as the measure of slack, over two separate decades (1996–2005 and 2006–2015), using industry-level price and employment gap data from the Canadian, World, Japanese, and EU-US KLEMS (capital [K], labour [L], energy [E], materials [M] and service [S]) datasets. Next, they regress the estimated slope and intercept coefficients on country-decade pairs of robot adoption rates, including industry, country and decade dummies.

[5] The increased access to information through the internet could also affect the formation of inflation expectations. In a version of the model featuring both forward-looking (or "rational") and backward-looking agents, this would also have implications for the expectations channel.

can be positive or negative, depending on whether digitalization promotes or hinders competition and product differentiation.

As discussed in Chu, Dahlhaus and Hajzler (forthcoming), **the direct empirical evidence on the relationship between digitalization and markups indicates that a positive impact is more likely. However, the few studies examining the effects of digitalization in the context of an empirical NKPC model have mixed results, and some tend to find the opposite effect**. For example, in a country panel regression analysis, Csonto, Huang and Tovar (2019) find a small but statistically significant negative coefficient when including a linear digitalization term in the NKPC. Specifically, they find that the direct effect of digitalization was a reduction in average annual inflation of about 0.05 percentage points between mid-2012 and the end of 2017. The European Central Bank (ECB) (2021) follows Bobeica and Sokol (2019) and estimates a large number of alternative Phillips curve specifications for the euro area. It augments the models with linear digitalization terms based on various measures of digital intensity (covering diverse aspects of both household and firm usage).[6] Similar to Csonto, Huang and Tovar (2019), the ECB also finds that, on average over 2013–19, digitalization lowered annual inflation in the euro area by around 0.05 percentage points. Interpreting these findings through the lens of the model discussed in **Box 1**, one might conclude that digitalization contributes to lower inflation by reducing markups. However, this interpretation is likely too simple. In a more general environment, the markup term in the NKPC captures all factors related to digitalization that impact inflation through channels other than economic slack or inflation expectations. The negative effect could instead reflect the cost-reducing productivity improvements discussed in Mollins and Taskin (2023) and Chu, Dahlhaus and Hajzler (forthcoming).

Friedrich and Selcuk (2022) also find that digitalization is associated with lower intercept terms when country dummies are excluded from the model, but the relationship turns positive once they are included. This suggests that the markup channel dominates the effects of lower production and entry costs, which is in contrast to Csonto, Huang and Tovar's (2019) findings. A possible reason for the discrepancy in these findings is that, in the case of robot adoption, causation runs in the opposite direction: in countries where labour costs are rising the fastest (leading to higher inflationary pressures), the incentives to automate are also stronger. This is an important question for future research.

Taken together, the narrow literature quantifying the effects of digitalization on the Phillips curve finds some evidence that digitalization increases the slope, at least when proxied by robot adoption. This is consistent with digitalization reducing price frictions and

[6] The proxies for digitalization on the household side include intensity of internet use, frequency of online purchases, and variables capturing online purchases by item categories. On the firm/retailer side, they include providing a description of the item sold online, allowing consumers to place orders, and allowing consumers to track their orders. To overcome the low frequency of the various digitalization measures, the series are converted to quarterly data using cubic spline interpolation. Rather than exploit variation across countries to estimate robust impacts based on a single digitalization measure, as in Csonto, Huang and Tovar (2019) and Friedrich and Selcuk (2022), the ECB estimates 7,128 models that differ in terms of the variables included (e.g., slack measure, inflation expectation measure or digitalization proxy) and focuses on the average estimates across all models.

rigidity. The findings for the cost-reduction, pro-competitive channels are mixed, but on balance indicate that a small negative impact on inflation is likely.

Box 1

Impacts of digitalization on the New Keynesian Phillips Curve

Many of the channels through which digitalization can impact inflation can be better understood through the lens of the New Keynesian Phillips Curve (NKPC) (Chu, Dahlhaus and Hajzler, forthcoming). To facilitate the connection between digitalization and model parameters, we start with a brief summary of the analytical solution to the NKPC in the standard framework, which is the foundation of the empirical Phillips curves underlying most central bank projection models. Implications of digitalization for aggregate inflation are then conveniently summarized by linking the channels considered in this paper to the structural parameters contained in the analytical expression for the NKPC.

The key equations summarizing the basic New Keynesian model are derived from the solutions to two problems:

- A representative household maximizes its welfare by consuming goods and leisure subject to its budget constraint.
- A large number of *ex ante* identical, monopolistically competitive firms maximize profits by setting optimal prices, taking into account consumer demand for their products, and subject to constraints on price setting. These constraints capture price adjustment costs that lead to price stickiness. They are conveniently modelled as an exogenous, positive proportion of firms ($\theta > 0$) randomly being constrained from adjusting their prices in any given period (referred to as Calvo staggered price adjustment).

The solution to the standard model yields the canonical expression for the NKPC that summarizes inflation dynamics. This expression relates inflation, π_t, to expected future inflation and the output gap, defined as the deviation in log output (y_t) from its steady-state level (y_t^n):[1]

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \kappa(y_t - y_t^n), \qquad (1\text{-A})$$

where $\beta > 0$ and $\kappa > 0$ are structural parameters (which are discussed in more detail below). The inverse of the output gap captures the degree of economic slack. Specifically, when aggregate output exceeds the steady-state level—the latter representing the amount of output that would prevail if all firms could flexibly adjust their prices—firms operate at above-average marginal costs and positive price pressure builds.[2] Intuitively, an economic shock that leads to higher aggregate demand and an increase in firms' optimal prices will result in firms simultaneously looking to increase prices and production. Because prices are rigid and firms are constrained from universally and instantly adjusting them, those firms that are unable to adjust prices meet demand by adjusting production above what is optimal in the long run (that is, after prices fully adjust). Moreover, current-period inflation is positively related to next-period inflation because firms that are in a position to increase prices today respond to higher expected future competitor prices (or production costs), since their next price adjustment may not occur for some time.

Box 1 (continued)

In the classic textbook version of the New Keynesian model of Galí (2008), the slope parameter κ is given by:

$$\kappa = \left(\frac{(1-\theta)(1-\theta\beta)}{\theta+\theta\epsilon\left(\frac{\alpha}{1-\alpha}\right)}\right)\left(\sigma + \frac{\eta+1-\alpha}{\alpha}\right) > 0, \tag{1-B}$$

where ϵ is the price elasticity of demand, η is the elasticity of labour supply to a rise in wages, and $1-\alpha$ is the labour share in aggregate production. This expression is decreasing in the measure of price stickiness θ, increasing in the labour share and decreasing in the elasticity of demand (see the Appendix for details). **Table 1-A** summarizes the potential effects of digitalization on the slope of the NKPC as a result of its hypothesized influence on these structural parameters.

It is also useful to consider a slightly generalized version of the NKPC to account for short- to medium-term changes in desired markup μ. Specifically, the relationship in equation (1-A) holds when the desired markup is assumed to be constant over time.[3] (In the basic model, the desired markup is a function of the elasticity of demand, which is also assumed to be constant.) However, the short-run implications of digitalization for markups are also of interest, given that changes in steady-state markups could impact inflation independent of the degree of economic slack. Including an additional term, $\gamma(d_t)$, with equation (1-A) captures the impact from transitory changes in markups associated with digitalization d_t:[4]

$$\pi_t = \underbrace{\beta E_t\{\pi_{t+1}\}}_{\substack{\text{Expectations} \\ \text{channel}}} + \underbrace{\kappa}_{\substack{\text{Slope} \\ \text{channel}}} \underbrace{(y_t - y_t^n)}_{\substack{\text{Slack} \\ \text{channel}}} + \underbrace{\gamma(d_t)}_{\substack{\text{Markup} \\ \text{channel}}} \tag{1-C}$$

The augmented NKPC relationship in equation (1-C) summarizes the four main channels through which digitalization could impact inflation in a standard New Keynesian model.

Box 1 (continued)

How digitalization might impact the New Keynesian Phillips Curve

The hypothesized directions of impacts are summarized in the table below.

Table 1-A: Hypothesized impacts of digitalization on the New Keynesian Phillips Curve

Parameter	Description	Predicted impact	Details
Slope channel		**Effect on slope**	
θ	Nominal rigidity (i.e., price stickiness)	+	Digitalization increases price flexibility (e.g., online firms), which reduces the degree of price stickiness (θ) and increases the slope.
ε	Elasticity of demand	-	If digitalization increases the range of substitutable varieties of goods, it will increase the elasticity of demand and flatten the slope.
$1-\alpha$	Labour share/ labour elasticity of output in the production function	+/-	Digitalization can reduce the labour share through labour-saving efficiency gains and economies-of-scale effects or increase the labour share through factor-biased technical change. A higher labour share is associated with a steeper slope.
κ	**Slope of Phillips curve**	+/-	Overall positive or negative slope impact, depending on whether price flexibility impacts of e-commerce dominate the effects of greater variety, or whether digitalization increases or decreases the labour share.
Slack channel		**Effect on output gap**	
$(y_t - y_t^n)$	Output gap	-	Digitalization tends to be productivity-enhancing. In the standard New Keynesian model with nominal rigidity, potential output increases in tandem with productivity gains but actual output responds more gradually, resulting in a narrower output gap.
Expectations channel		**Effect on expected inflation**	
$E_t\{\pi_{t+1}\}$	Expected inflation	+/-	Inflation expectations can deviate from target if supply or technology shocks (driven by digitalization) are not perfectly offset by policy. The impact depends on whether digitalization increases inflation (via higher markups) or decreases it (via higher potential output and lower marginal costs). Digitalization can also help anchor expectations. This could also lower inflation expectations in the case of upward bias in household expectations.

Box 1 (continued)

Markup channel		Effect on markups	
$\gamma(d_t)$	Desired markup	+/-	On one hand, digitalization can result in a larger number of product varieties, more intense competition and lower markups. On the other hand, it can promote the rise of superstar firms and higher markups (see section 4 for details).[5]

[1] See the Appendix for an overview of the model and derivation of the NKPC.

[2] The steady-state level of output is also commonly referred to as the natural rate of output.

[3] Intuitively, an increase in the desired markup over marginal costs would imply a higher steady-state price level but does not have any long-run impacts on inflation other than its implications for the slope.

[4] In the literature, this additional term is generically referred to as a *cost push shock*. More generally, this term captures any transitory deviation between the flexible price equilibrium and efficient allocation that is independent of the output gap.

[5] It is important to note that, from the standpoint of a more general model, the markup variable $\gamma(d_t)$ captures all factors related to digitalization that impact inflation through channels other than economic slack or inflation expectations. This presents certain challenges when empirically estimating the relationship (1-C). For example, the negative effects of productivity improvements on inflation that are hypothesized to operate through the slack channel (coinciding with an increase in potential output and lower marginal costs of production) could be partially captured in $\gamma(d_t)$ if potential output is mismeasured.

1.2 Potential output and economic slack

In the context of the New Keynesian model, a sudden acceleration in digitalization can be interpreted as a persistent technology shock, whereby the adoption of productivity-enhancing capital and production processes by firms leads to higher current and expected future potential output, captured by y_t^n in equation (1). In the absence of nominal price rigidities, output would instantly increase to the new level of potential output, with no impact on the output gap, inflation or monetary policy. However, when prices adjust only gradually, the basic New Keynesian model predicts that growth in actual output will lag behind the change in potential output, resulting in a widening of the output gap (in the direction of greater excess supply) and lower inflation.

When the Canadian economy is operating under a positive output gap, aggregate demand is inefficiently high relative to available supply, and monetary policy tightening is needed to counteract the resulting inflationary pressures. **In this context, a sudden productivity-boosting acceleration in adoption of digital technology would increase potential output. Until aggregate demand catches up, this can ease the burden on monetary policy to close the output gap.** As discussed in Mollins and Taskin (2023), such productivity improvements, if they exist, are difficult to quantify. Evidence suggests that adoption of some forms of digital technology has accelerated over the course of the COVID-19 pandemic. However, aggregate capital accumulation and growth in total factor productivity have been relatively weak since 2019, though possibly not as weak as they might have been without digitalization. Digitalization could also reduce inflationary pressures through the slack channel in other ways. For example, in times of excess demand, aspects of digitalization that improve match efficiency in labour markets could help reduce the duration of unemployment, thus helping to close the gap more quickly.

1.3 Inflation expectations and how digitalization matters for central bank communications

In influencing labour productivity and economic slack, digitalization could also directly impact inflation expectations. Specifically, an acceleration in adoption of digital technology can be interpreted as a persistent technology shock that not only boosts productivity and potential output in the current period but also feeds into expectations of higher productivity and lower prices in the future. If the monetary authority is unable to immediately offset such shocks by easing monetary policy, firms will tend to reduce current prices and both households and firms would expect future inflation to fall.[7] For an inflation-targeting central bank like the Bank of Canada, the resulting downward pressure on inflation would likely call for a more accommodative monetary policy stance, all else being equal.

These implications assume that both consumers and price-setting firms condition their expectations of future prices on macroeconomic developments and that they are aware of monetary policy objectives and reaction functions. However, central banks do not take this for granted. They increasingly reach out to the public to motivate and explain their monetary policy actions, not only to ensure accountability and create trust but also to help guide expectations.[8] This suggests another important way in which digitalization can affect monetary policy. By expanding central bank communications channels and the ways information is transmitted, digitalization can impact expectations about the path of future interest rates and the economy as well as consumer behaviour.

Digitalization offers new forms of communication for central banks: outreach through websites, presence on social media (Twitter, Facebook, LinkedIn, YouTube), and events relayed by Twitter and YouTube. The literature on the impact of digitalization is still in its infancy and quickly evolving. Among the targets of central bank communications, two groups must be distinguished: expert groups—particularly financial market specialists—and the general public. The former pays close attention and understands the central bank's communications, but communicating with the latter presents challenges (Blinder et al. 2022).

Financial market specialists and professional forecasters listen to central bank communications intently. As a result, **their long-term expectations seem to be aligned with central banks' inflation targets**. However, Coibion and Gorodnichenko (2015) present evidence from estimated Phillips curves that households' forecasts are better proxies for firms' forecasts than professional forecasts are, which points to the importance of the general public's expectations.

[7] The increased access to information through the internet could also affect the formation of inflation expectations. In a version of the model featuring both forward-looking (or "rational") and backward-looking agents, this would also have implications for the expectations channel.

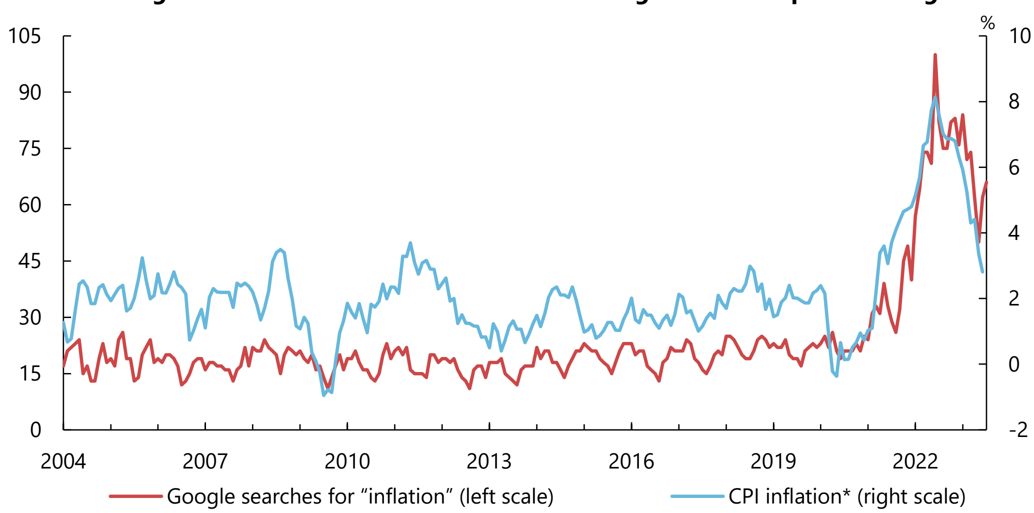
[8] According to Blinder et al. (2017), more than 80% of central bank governors indicated in a 2016 survey that their communications had intensified since the 2008–09 global financial crisis, and a clear majority expected these changes in communication practices to remain or go further.

Reaching the general public is challenging, mainly because people pay limited attention to central bank communications and broader economic developments that do not figure prominently in their day-to-day financial decisions. Households will pay less attention if they do not understand the central bank's goals or how its policies impact them personally or the economy (Binder 2017; van der Cruijsen, Jansen and de Haan 2015). Moreover, the success of monetary policy in keeping inflation low and stable over the past 30 years has likely contributed to higher inattention among households and firms. Similarly, the increase in inflation at the end of 2021 produced a renewed interest in the topic. This is illustrated in **Chart 1**, which shows that the number of Google searches in Canada for the word "inflation" increased when inflation rose in the second half of 2021.

Digitalization can help central banks reach larger audiences compared with traditional communications channels. This, in turn, has the potential to increase public awareness of a central bank's monetary policy goals and contribute to more precise inflation expectations.

So far, digitalization does not seem to have had a strong impact on how households obtain their information about monetary policy. Traditional media—especially television and the printed press—still remain the most important sources of information about the ECB for households in the euro area. Gardt et al. (2022) note that online press is the only digital media in the top five information channels. Those authors also show that internet blogs and forums, the ECB's website and social media are not important sources of information. However, digital media are still relatively new and, in all likelihood, will grow in importance.

Chart 1: Google searches for "inflation" increased during the recent episode of high inflation



*Year-over-year percentage change

Note: Numbers on left scale represent search interest relative to the highest point on the chart for the given region and time. A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A value of 0 means not enough data were available for this term.

Sources: Google Trends and Bank of Canada calculations

Last observation: June 2023

Digital platforms such as Twitter opened up new avenues to reach audiences. Most central banks communicate on Twitter and can have many followers.[9] Gorodnichenko, Pham and Talavera's (2021) analysis of the Federal Reserve System's communication on social media suggests that economists and media are more active than other groups of users. While a large share of them are interested for professional reasons, this channel offers substantial potential to reach the public. Social media reach people more directly than other media but offer little control over the content of online discussions. Ehrmann and Wabitsch (2022) show that tweets about the ECB generally become more factual in response to its communication. However, tweets are also more likely to be shared if they are less factual.

While digitalization offers potentially important channels to reach a non-specialist audience, **central bank communications need to target audiences better and use plainer language than they currently do.** As Blinder et al. (2022) discuss, to communicate with non-experts, central banks have a few tools in their tool kit:

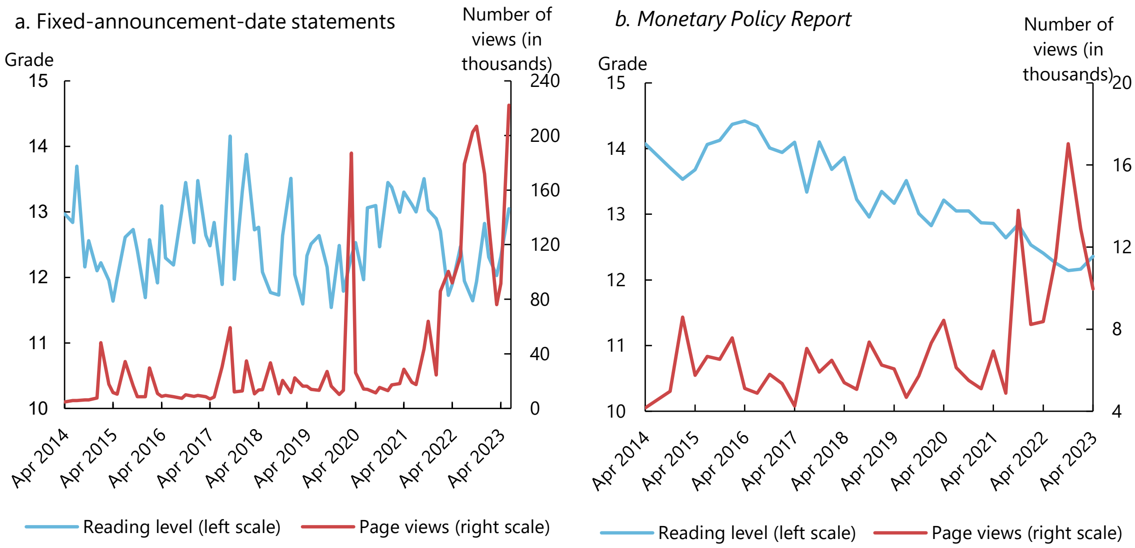
- economic education in the form of layered communications, which allows the public to learn about monetary policy in simple terms and leaves jargon and more complex material for experts
- short and clear pieces of text on specific issues related to the central bank's tasks and activities

Text analytics can help evaluate the readability of central bank publications and guide efforts to improve them, as in Binette and Tchebotarev's (2019) analysis of the Bank of Canada's *Monetary Policy Report* (MPR). Also, data collected from users' activity on a central bank's website can help the central bank improve its communication. As **Chart 2** illustrates, better readability in fixed-announcement-date statements and MPRs seem to be associated with a higher website viewership (the correlations are -0.57 and -0.22, respectively).[10]

[9] The Bank of Canada has more than 200,000 followers on Twitter as of November 2022.

[10] The correlations between MPR page views and reading level remain when adjusting for the trend in readability or removing the last five observations, but are not as high.

Chart 2: Improved readability is associated with an increased number of Bank of Canada page views



Note: Readability level corresponds to the education grade level required to understand the text. It is calculated using the mean of different readability measures: Flesch–Kincaid Grade Level Formula, Coleman–Liau Index, Gunning Fog Index, Simple Measure of Gobbledygook, Automated Readability Index and Dale–Chall Readability Formula. Page views are calculated using the sum of page views up to seven days after the publication is released.

Sources: Google Analytics and Bank of Canada calculations

Last observations: panel a, June 2023; panel b, April 2023

2. Digitalization brings new data and techniques to support central bank decision making

Aside from affecting the transmission of monetary policy, digitalization also provides new ways to monitor the economy. Novel data of different types and sources are becoming available and proving useful, especially when it comes to obtaining a timelier and more holistic picture of the economy. Innovative techniques have been developed not only to improve forecasts but also to handle increasing volumes of data and extract information from previously untapped sources.

Alternative data, however, are noisier than traditional data, and machine learning techniques often lack transparency. The hope is that the rapid pace of innovation brought about by digitalization will continue to deliver techniques to improve the quality of data and better separate signals from noise.

2.1 New alternative data sources increasingly complement traditional data

Researchers and policy-makers have access to **more data than ever before** and have **better tools to manipulate and analyze them**. This trend is notable in the use of big data: more than 80% of central banks surveyed in 2020 reported using big data, compared with 30% five years earlier (Serena et al. 2021). Data have improved along several dimensions:

- Type—**New types of data** have become more abundant and easier to access, thanks to digitalization. These were not used before because they were not available (for example, mobility data generated from mobile phones) or the tools to extract information from the data were ineffective. In some instances, the necessary tools simply did not exist (for digital text, sound, images and video).
- Frequency—Data are often collected automatically, sometimes as a by-product of transactions, digital tracking of movement, or any interaction with Internet of Things products. These data can now be provided at a **high frequency**.[11]
- Timeliness—Some high-frequency data are also available in near real time. This **increased timeliness** is of great help to decision makers because traditional economic data are often available only with long lags.
- Detail—A **more granular view** of the economy can provide a holistic picture along geographical and household socio-economic dimensions. More detailed data can also shed light on specific markets.
- Coverage—Traditional data often rely on a limited sample size, whereas some non-traditional data often represent a large share of the population. This **improved coverage** allows for more disaggregated statistical analysis and alleviates potential concerns about sample representativeness.

These improvements are closely connected to digitalization, which decreases the costs of data collection and communication. In some cases, such as for organic data (data that are collected as a by-product of other activities), the acquisition cost is much lower than for data from traditional sources (e.g., surveys). As a result, practitioners now have access to more and cheaper (or free) data than ever before.

Yet challenges do exist for working with digitally curated data. Storing and manipulating massive amounts of data requires an **appropriate information technology (IT) infrastructure** with enough computing power and storage capacity as well as adequate security. Big data present their own challenges; special software, methods and algorithms are often needed due to the size of the data.

Non-traditional data are often noisier than data from traditional sources because they are curated less. That is, the "noise"—or random measurement errors—in such data tends to be comparatively high, implying that the quality of the "signal" conveying the information we are ultimately interested in is comparatively low. As a result, the signal-to-noise ratio, which measures the strength of the desired signal relative to background noise, is usually lower than for data from traditional sources. These non-traditional data also tend to suffer from sample selection bias,[12] especially in the case of organic data, which are increasingly being used to complement gross domestic product (GDP) data from traditional sources. Often being of lesser

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[11] The Internet of Things refers to the network of physical objects that exchange data or commands over the internet, made possible by equipping them with sensors, software and other digital technology. These devices range from modern household appliances and automobiles to sophisticated industrial tools.

[12] For example, transaction data from credit card providers will not capture payments using cash, debit cards or e-transfers. This is especially problematic when some socio-economic groups are underrepresented or absent, as is the case in this particular example, in which older people and those with lower incomes might not have access to credit cards.

quality and lacking proper methodological documentation, non-traditional data require a significant amount of cleaning as well as validation with traditional data. An additional difficulty when working with high-frequency time series is how to adjust for seasonality. While methods to seasonally adjust monthly data are well established and easy to use, consensus has not yet been reached on how to de-seasonalize high-frequency data.[13] The challenges are multiple: integer periodicity, multiple periodicity and moving holidays. For example, in the case of a weekly time series, one has to deal with a variable number of weeks in a year, intra-monthly and intra-yearly periodicity, and Easter occurring in a different week depending on the year.

However, the advantages listed above (i.e., low cost, timeliness, frequency, coverage and granularity) compensate for these weaknesses. **In turbulent times, timeliness is key and large changes are easily detected despite noise in the data**, which make these non-traditional data especially valuable. For example, Chart 6 in Chernoff and Galassi (2023) illustrates how Bank of Canada staff are using Indeed job postings data, which are available two to three months before the related statistics from Statistics Canada's Survey of Employment, Payrolls and Hours are released. Having timely access to data on labour demand helps the monetary policy decision-making process, particularly during periods when the dynamics of labour markets are rapidly changing.

2.2 Data science and machine learning are slowly becoming part of central banks' tool kits

The explosion of data has been accompanied by the development of new tools and techniques that not only made it possible to create the data but also to extract insights from them. Data science and machine learning, as well as IT innovation in general, offer many **new techniques** to:

- **collect and assemble data**, such as through automated pipelines, web-scraping and approximate string matching to merge datasets that have not been curated for that purpose
- **extract patterns and produce forecasts** with machine learning algorithms ranging from simple models based on linear regression to highly complex deep learning models
- **process text, audio, images and video** through specialized machine learning models that can deliver insights from these underused sources of data
- **communicate information** using notebooks that combine code, explanations, results and interactive visualizations on dashboards

Despite the many benefits of these techniques, predictions based on machine learning algorithms need to be treated with caution. While machine learning algorithms can excel at finding patterns in data and forecasting, they tend to be "black boxes," especially the more sophisticated ones. That is, it can be difficult or even impossible to understand how an

[13] X13 seems to be the most common seasonal adjustment software; it is freely available at the website for the United States Census Bureau.

algorithm delivered its prediction. This makes it **risky to base policy decisions on these predictions** for several reasons:

- Compared with traditional approaches, complex models often **lack transparency** and have a higher likelihood of capturing spurious relationships, which is problematic when policy-makers need to be able to explain their decisions.
- Complex models fit patterns in the data better than traditional models but are also more **prone to overfitting**, in which case they do not generalize to unseen data.[14]
- In cases of structural changes in the economy, a model trained on data collected before the changes **might deliver incorrect predictions**.[15] (This is also true for traditional models but becomes more of a concern if how these predictions are made is unknown.)

Aside from these concerns, **some machine learning models require an enormous amount of data, considerable computing power and skilled data scientists to run them**. The lack of data is often most acute in areas for which these models have not been designed, such as macroeconomic policy questions. State-of-the-art deep learning models like those used in natural language processing require immense computing power, which is available only to the biggest technology companies.[16] This makes them too expensive to train for most organizations. However, pre-trained versions of these models are often available from an open source, which mitigates the problem.

Finally, the combination of skills required to run these models and statistics, programming and domain expertise (economics and finance for central banks) is scarce. The **shortage of talent makes hiring in this domain difficult and expensive**. Nevertheless, considerable efforts are underway to make these models easier to use and to educate the public with online resources such as blog posts, tutorials and courses. Also, teaching machine learning tools is becoming more common in quantitative disciplines and will become part of economists' toolboxes.

Thanks to data science and machine learning techniques, **non-traditional data are increasingly being used to complement official data in monetary policy analysis.** Machine learning techniques enable central banks to use more timely information. They also allow central bank researchers to exploit previously untapped information to gain deeper insights into both the real and financial sides of the economy and into the channels through which monetary policy operates. Together, data science, machine learning techniques and non-traditional data are ultimately changing the way the Bank thinks about the economy and financial system.

One example of the use of non-traditional data at the Bank is **unstructured text data that shed light on various economic events and inflation expectations**. News-based indicators track labour and supply shortages using text analytics algorithms on a large database of

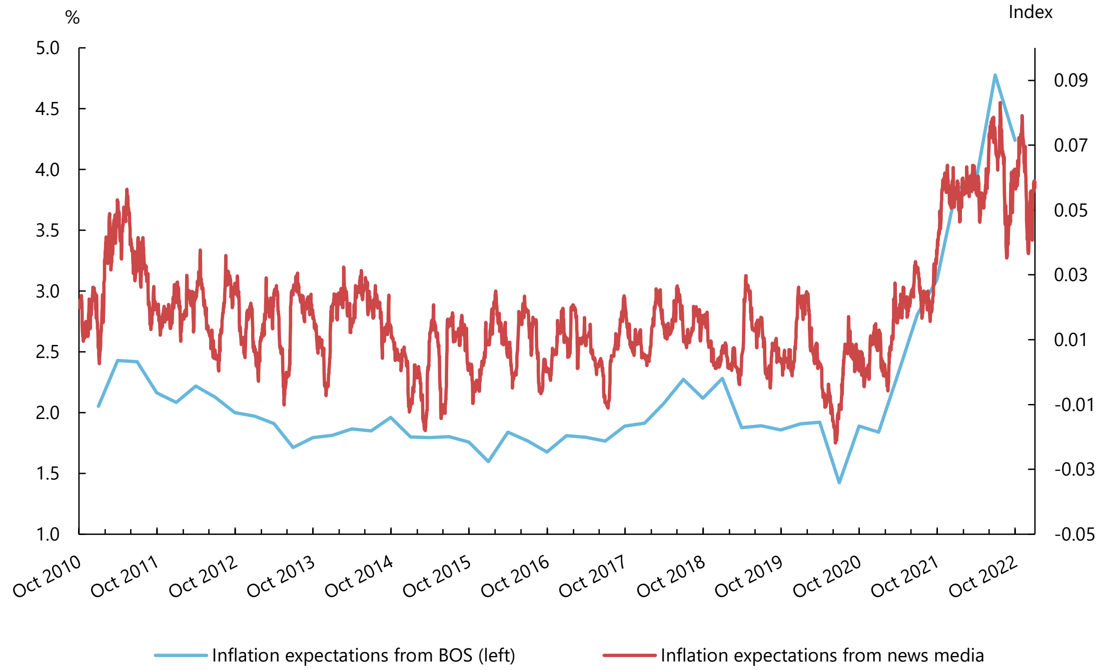
[14] Overfitting occurs when a model fits too closely to a particular set of data and may therefore fail to predict future observations reliably.

[15] Training a model involves adjusting the model's parameters to optimize its performance on a certain task (prediction in this case).

[16] Natural language processing is a subfield of linguistics, computer science and artificial intelligence concerned with programing computers to process and analyze natural language data.

Canadian newspapers (see Chen and Houle 2023). The same data and similar techniques were also used to develop indicators of inflation expectations, as shown in **Chart 3**.

Chart 3: Real-time, news-based indicators of inflation expectations mirror those in the Business Outlook Survey



Note: BOS is Business Outlook Survey. "Inflation expectations from BOS" are quarterly data that have been multiplied by 100. "Inflation expectations from news media" are daily data that have been resampled to a 30-day moving average. The inflation expectations index is a composite measure of (i) media attention on the topic of inflation expectations and (ii) the implied direction of those inflation expectations (increasing or decreasing). The media attention element is determined by applying a topic model to Canadian news media and extracting the topic of inflation expectations. A score is assigned to each word or phrase used by the media; words and phrases that are more closely related to the topic of inflation expectations receive a higher score. The five highest-scoring sentences are then assessed for directionality—whether inflation expectations are increasing or decreasing. For more information on how topic models are used in a similar context, see L. Chen and S. Houle, "Turning Words into Numbers: Measuring News Media Coverage of Shortages," Bank of Canada Staff Discussion Paper No. 2023-8 (March 2023).

Sources: Business Outlook Survey, Cision Media Database and Bank of Canada calculations

Last observations: BOS, 2022Q4; news media, January 2023

Other text data have also proven useful in monitoring inflation expectations. For example, using tweets in Italian, Angelico et al. (2022) construct real-time measures of inflation expectations. They show that the extracted indicators constitute a good proxy for inflation expectations and contain additional information beyond market-based expectations, professional forecasts and realized inflation.

New indicators, such as those based on transaction or movement data, are displayed on dashboards and can be used in nowcasting. During the pandemic, alternative data were immensely useful to gain information about the effects of lockdowns and other restrictions on the Canadian economy. For example, mobility indicators were provided by Google and Apple,[17] real-time data about COVID-19 cases and hospitalization were available at the country and

[17] Google's mobility data are no longer updated, and Apple mobility data are no longer available.

regional levels, and restaurant reservations could be tracked using data from OpenTable.[18] All these data were displayed on interactive dashboards and automatically updated.

3. Important future trends and open questions

Just as digitalization is revealing vast sets of data and new tools for analyzing the economy, it also presents new challenges for policy-making. In particular, macroeconomic analysis and forecasting face at least two challenges that could be magnified as digitalization expands:

- As opportunities to mine new sources of granular and high-frequency data expand—particularly as the costs of storing and manipulating large quantities of such data decline—more effort is required to filter out the noise and restructure the information so it can be used as part of a central bank's policy tool kit.
- Given the importance of being able to accurately measure the real economy for monetary policy, the significant challenges in measuring the scope of digitalization and in capturing its impacts on productivity, labour markets and prices, could increase the possibility of monetary policy errors.

The first of these challenges is likely to diminish over time, although at a gradual pace. As discussed in the previous section, advancements in machine learning (and in artificial intelligence more broadly) allow researchers to develop more powerful algorithms for analyzing large quantities of data and to ensure that the economic information extracted from them is sufficiently reliable and representative. And as these techniques become integrated in economics and statistics curricula, it should become easier for central banks to find the right skills and human capital to effectively leverage this information. However, as Benoît Cœuré of the ECB noted in a 2017 speech, many other employers are competing for the same skills, and recruiting these highly sought-after experts may prove challenging for years to come.[19] In the interim, the risk exists that poor quality data sources can drive out better ones in public discourse, especially if the former are timelier. Specifically, individuals might shift toward relying on readily available, third-party data sources. This could undermine confidence in official statistics, which have traditionally been subject to greater scrutiny but are typically published with a lag (Nymand-Andersen 2016).

The second of these challenges could become more pronounced over time. As discussed in Faucher and Houle (forthcoming), while the many alternative ways of measuring the digital economy have their limitations, their existence points to the growing relative importance of digitalization in overall economic activity. Given the inherent challenges in measuring digitalization, the problem of mismeasurement could also become more severe. Growth in long-term output or value added could be underestimated as consumers substitute away from paid, tangible products, to free or quasi-free digital products, or as hard-to-measure quality improvements in digital technology become more pronounced in industrial production and consumption baskets. This would lead to a downward bias in potential output estimates relative

[18] See the OpenTable website.

[19] B. Cœuré, "Policy analysis with big data," (speech delivered at the Economic and Financial Regulation in the Era of Big Data conference, Paris, France, November 24, 2017).

to GDP, giving the appearance of less economic slack than would be apparent if the contributions from digitalization were fully accounted for. Moreover, when growth has been understated due to unmeasured quality improvements, the price index and hence inflation will generally have been overstated by a roughly similar amount. These measurement issues have implications for how central banks assess their monetary policy stance during periods of rapid digital transformation (IMF 2018) and could even lead to missteps in the timing of monetary policy decisions.

Continued research on the implications of digitalization for monetary policy will enhance central banks' ability to navigate these complex issues. We conclude with a list of key topics for future research to inform monetary policy and to prepare for the challenges ahead:

- How does digitalization affect the transmission of monetary policy? Work to understand the implications of digitalization for the NKPC is in its infancy, and further research on the quantitative importance of possibly offsetting channels will help shed light on this question.
- What is the best way for a central bank to communicate on social media and control the spread of misinformation and disinformation by users?[20]
- Alternative data are often timelier but of lesser quality than traditional data. Given that both timeliness and accuracy of data are important for a central bank's decisions, how should that trade-off be handled?
- Despite a lot of work to make them more interpretable, state-of-the-art machine learning algorithms still lack transparency. Given the issues this creates, as discussed above, what role should machine learning algorithms have in supporting a central bank's decisions?

[20] Both misinformation and disinformation consist of spreading false information, deliberately in the latter case.

Appendix: Deriving the New Keynesian Phillips Curve

The key equations summarizing the basic New Keynesian model are derived from the solutions to two problems:

1. A representative household maximizes its welfare from consuming goods and leisure subject to its budget constraints.
2. A large number of *ex ante* identical, monopolistically competitive firms maximize profits by setting optimal prices, taking into account consumer demand for their products and subject to constraints on price setting. These constraints capture price adjustment costs that lead to price stickiness and are conveniently modelled as an exogenous, positive proportion of firms ($\theta > 0$) randomly being constrained from adjusting prices in any given period (referred to as the Calvo staggered price adjustment).

In this framework, when firms do get to reset their prices, they take into account that their prices may be fixed for many periods. The optimal price (expressed in natural logarithms) set by a firm that is able to adjust its price in period t is summarized by equation (A-1):

$$p_t^* = \mu + (1-\theta\beta)E_t \sum_{k=0}^{\infty} \theta^k \beta^k mc_{t+k}^n(t)\,, \tag{A-1}$$

where E_t denotes expectations at time t and β is the rate of time discount. Here μ is the desired markup over nominal marginal costs and $mc_{t+k}^n(t)$ is the (expected) nominal marginal costs of production in period $t+k$ (i.e., k periods into the future) of a firm that sets its price in period t, both expressed in natural logs. Intuitively, firms that are able to reset their prices choose a price equal to their desired markup over a discounted weighted average of current and expected future marginal costs, where the weights reflect the geometrically decreasing likelihood of being stuck with that price k periods into the future.

The (log) price level is the weighted average of the proportion θ of prices that are unchanged from the previous period and the prices set by the proportion $1-\theta$ of firms that reset their price in that period:

$$p_t = \theta p_{t-1} + (1-\theta)p_t^*.$$

Similarly, the inflation rate in each period, π_t, is a weighted average of the rate of the θ zero-rate of price change and the $1-\theta$ re-optimized price changes:

$$\pi_t = \theta[p_{t-1} - p_{t-1}] + (1-\theta)[p_t^* - p_{t-1}] = (1-\theta)[p_t^* - p_{t-1}]. \tag{A-2}$$

Assuming a simple, identical concave production technology for all firms, $y_t = a_t + (1-\alpha)n_t$ (where y_t is log output, a_t is a total factor productivity parameter, n_t is log labour input, and $1-\alpha$ is the labour income share in production), one is able to show that:

$$mc_{t+k}(t) = mc_{t+k} - \tfrac{\alpha\epsilon}{1-\alpha}(p_t^* - p_{t+k}), \tag{A-3}$$

where $mc_{t+k} = mc_{t+k}^n - p_{t+k}$ is real marginal costs in period $t+k$ and ϵ is the price elasticity of demand for each product variety. (See Chapter 3 of Galí [2008] for derivation details.)

Substituting equation (A-3) into equation (A-1) and rearranging terms yields the following difference equation (after some algebraic manipulation):

$$p_t^* - p_{t-1} = \beta\theta E_t[p_{t+1}^* - p_t] + (1-\beta\theta)\,\Lambda[mc_t + \mu] + \pi_t, \qquad \text{(A-4)}$$

where $\Lambda = (1-\alpha)/(1-\alpha+\alpha\epsilon) < 1$ and the term in brackets, $mc_t + \mu$, is the difference between real marginal cost (that is, $mc_t = mc_t^n - p_t$) and its steady-state value $-\mu$ (that is, the long-run value of marginal costs that would prevail after all firms have had the opportunity to adjust their prices).[21] Finally, using the expression for π_t given by equation (A-2) to solve for $p_t^* - p_{t-1}$ and substituting into equation (A-4) yields a simple expression for inflation dynamics (after some algebraic manipulation):

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \lambda(mc_t + \mu), \qquad \text{(A-5)}$$

where $\lambda = \frac{(1-\beta\theta)(1-\theta)}{\theta}\Lambda > 0$ and $E_t\{\pi_{t+1}\}$ is the expected inflation rate in the next period. That is, current-period inflation is positively related to both expected future inflation (given that higher expected future competitor prices encourage higher price increases among those firms that have an opportunity to change them today) and to increases in marginal costs above their long-run values.[22]

It turns out that the model predicts a one-to-one, long-run relationship between $\mu + mc_t$ and the deviation in log output (y_t) from its steady-state level (y_t^n), which is a common concept of the output gap, capturing the degree of economic slack. Here, steady-state output is also referred to as the natural rate of output—the amount of output that would prevail if all firms could flexibly adjust their prices in the current period. Substituting this relationship into equation (A-5) yields the following expression for the NKPC:[23]

$$\pi_t = \beta E_t\{\pi_{t+1}\} + \lambda\left(\sigma + \frac{\eta+1-\alpha}{\alpha}\right)(y_t - y_t^n), \qquad \text{(A-6)}$$

where η is the elasticity of labour supply to a rise in the wage rate. Combining the expressions for λ and Λ above, the coefficient on the output gap, the slope of the NKPC, is given by:

$$\kappa = \frac{(1-\theta)(1-\theta\beta)}{\theta}\,\frac{1}{1+\epsilon\left(\frac{\alpha}{1-\alpha}\right)}\left(\sigma + \frac{\eta+1-\alpha}{\alpha}\right) > 0. \qquad \text{(A-7)}$$

Following the European Central Bank’s (2021) approach, we also consider an alternative specification for the slope derived from Sbordone (2007), who generalizes the framework to allow firms’ elasticity of demand to depend on their relative market share:[24]

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[21] This derivation also uses the result that desired markups are approximately equal to the inverse of steady-state real marginal costs: $\mu = -mc$.

[22] Expected future inflation is, in turn, a positive function of expected future marginal costs. This recursive expression can be iterated forward to express inflation as the discounted sum of current and expected future deviations of real marginal costs from their long-run values.

[23] See Chapter 3 of Galí (2008) for a full derivation of the relationship between average marginal cost deviations and the economy-wide output gap.

[24] In the standard model, firms are assumed to face a constant elasticity of substitution regarding differentiated products of its competitors.

$$\kappa = \frac{(1-\theta)(1-\theta\beta)}{\theta}\frac{1}{1+\bar{\varepsilon}(s_y+\varepsilon_\mu)}\left(\sigma + \frac{\eta+1-\alpha}{\alpha}\right). \qquad \text{(A-8)}$$

Here, $\bar{\varepsilon}$ is the steady-state demand elasticity, s_y is the elasticity of marginal costs with respect to sales (sensitivity of marginal costs to the firm's own output), and ε_μ is the elasticity of markups to a firm's marginal costs (capturing the sensitivity of the firm's desired price to marginal costs relative to other prices).

Both expressions for the slope are decreasing in the measure of price stickiness θ, increasing in the labour share, $1-\alpha$, and decreasing in the elasticity of demand, ϵ, $\bar{\varepsilon}$. Furthermore, the specification in Sbordone (2007) is decreasing in both s_y and ε_μ. However, the net effect of an increase in the labour share is ambiguous in Sbordone's specification because, all else being equal, a higher labour share would tend to make a firm's marginal costs rise more in response to higher sales volumes (increasing s_y). This flattens the slope in Sbordone's version of the model, possibly offsetting the positive or negative impact through $1-\alpha$.

The impacts of digitalization on the standard Phillips curve given by the slope parameter in equation (A-7) is discussed in the main text. Here, we briefly discuss the additional implications based on the slope coefficient in Sbordone's model in equation (A-8).

- **Markup elasticity** (ε_μ): This is a decreasing function of the number of differentiated varieties of the consumption good. The adoption of digital technologies can increase the number of products, particularly as e-commerce and widespread internet use allow retailers to promote new varieties and sell large quantities of each product (Brynjolfsson, Hu and Smith 2003). This decreases ε_μ and steepens the NKPC.
- **Elasticity of marginal costs with respect to sales** (s_y): This elasticity is negatively related to the labour elasticity of production and, in turn, the labour share. That is, if digitalization contributes to a declining labour share, as is hypothesized in the standard model, this will tend to flatten the NKPC via an increase in s_y. Similarly, the widespread adoption of digital technologies tends to place greater emphasis on fixed costs in production, whereas the importance of variable costs diminishes. This also causes factor costs to fluctuate less with demand (Korinek and Ng 2017).

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