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Incidence of the Digital Economy and Frictional Unemployment

International Evidence

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Abstract

This paper is the first to quantify the relationship between the incidence of the digital economy and long-term frictional unemployment across countries. The resulting evidence indicates that there is a robust, negative partial correlation between national unemployment rates and the incidence of the digital economy, proxied by the share of the adult population that reports using the internet to pay bills. Further, the absolute values of ordinary least squares estimates of the partial correlation suggest that it might be higher for developing economies than high-income economies. Controlling for the incidence of informal employment appears to be key for removing a positive omitted- variable bias in the estimate of the partial correlation between unemployment and the digital economy, which is due to the existence of a negative bivariate correlation between unemployment and informality on the one hand, and a negative bivariate correlation between informality and the incidence of digital payment on the other hand. The results from instrumental variable estimations suggest that the partial correlation between unemployment and digital payments is negative, with the absolute value of the estimates being larger than the absolute value of the ordinary least squares estimates.

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Incidence of the Digital Economy and Frictional Unemployment: International Evidence

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I. Introduction

Advances in technology have transformed digital platforms into data driven matchmakers. Digital technology transforms information into bits, which ultimately reduces the cost of storage, computation, and transmission of data. This shift in costs - lower search, replication, transportation, tracking, and verification costs - enlarges the potential scope and quality of matches between economic agents, with the existing literature pointing to a variety of consequences for market structure (see Goldfarb and Tucker 2019). Of particular relevance for labor markets, the reduction in search-and-matching costs is likely to increase the quality and speed of matches between economic agents, namely employers and workers.

Furthermore, frictional unemployment is the informationally intensive portion of overall unemployment that occurs due to search-and-matching frictions that prevent available workers from instantly finding a potential employer. Frictional unemployment is thus the long-term component of unemployment that is not responsive to cyclical economic fluctuations in labor demand. Yet search costs are lower in digital environments than in the 20th century when digital tools were unavailable. Therefore, the key question addressed in this paper is: Is there a correlation between the incidence of the digital economy and long-term unemployment rates?

The literature on the potential impacts of digital technologies on market structure is already quite large and growing – see the review by Glodfarb and Tucker (2019). Unfortunately, the literature has a glaring blind spot when it comes to addressing the issue of unemployment. The closest contribution to the literature is the article by Hjort and Poulsen (2019), which studies the impact on local labor markets in African economies of the advent of high-speed internet. But this article is silent with respect to unemployment rates, although it does present estimates on local (sub-national) employment rates.

This paper explores the bi-variate and partial correlations between the incidence of the digital economy on frictional unemployment across the world. The empirics rely on international data from 2000-2017. The resulting evidence indicates that, after controlling for informality, the size or incidence of the digital economy – proxied by the share of the adult population that reports using the internet to pay bills – is negatively correlated with unemployment rates across countries. In addition, it is plausible that the negative correlation is stronger among developing economies than among high-income economies.

The rest of this paper is organized as follows. Section II provides a brief review of existing literature. Section III presents the data and discusses the proxy variables used to capture the incidence of the digital economy. Section IV lays out our empirical strategy and presents the results. It begins with non-parametric estimations of the bi-variate relationship between unemployment and the digital economy across countries, followed by a discussion of an apparent omitted variable bias due to the incidence of informality in developing economies, which leads to the specification of simple OLS and IV econometric models to estimate the partial correlation between unemployment and the digital economy. Section V concludes.

II. Literature Review

While there is little literature on the effects of the digital economy on frictional unemployment, new evidence has emerged regarding employment and the role of digital payments, particularly in developing countries. Hjort and Paulsen (2019) studied the gradual arrival of submarine Internet cables on the coast of Africa and investigated the effects of the Internet on employment in local labor markets. In each of the three different data sets that together cover 12 African countries with a combined population of roughly half a billion people, the authors find a significant and large relative increase in the employment rate in connected areas when fast Internet becomes available, with little to no job displacement across space. In 8 countries for which the authors use Demographic and Health Survey (DHS) data, they find a 6.9 percent increase in the probability that an individual is employed when fast Internet arrives. In 9 countries with Afrobarometer data, there is a 13.2 percent increase in the employment rate when fast Internet arrives. Finally, in South Africa, using Labor Force Survey (LFS) data, there is a 3.1 percent increase in the employment rate with the arrival of fast Internet. The impact is driven by increased employment in higher skill occupations, as less educated workers' gains are smaller; estimated increase in employment in a skilled occupation is biggest for those with tertiary education. Overall, those with only primary schooling also see increased employment but only in unskilled occupations. The observed changes in use of Internet suggest two things: new types of jobs may have been created both via new Internet users as well as different use of Internet by existing users.

Bachas et al (2018) research the effects that payments systems can have on employment in Mexico, specifically studying a natural experiment in which debit cards tied to existing savings accounts were rolled geographically over time to beneficiaries of the Mexican cash transfer program, *Oportunidades*. Prior to receiving debit cards, beneficiaries received transfers into a savings account every two months. After receiving debit cards, beneficiaries continued to receive their benefits in their savings account, but can access their transfers and savings at any bank's ATM. In Mexico, transaction costs can be a significant barrier to the use of formal financial services; account opening fees and minimum balance requirements prevent poor households from opening bank accounts. The facilitated access to finance through debit cards significantly reduced the median road distance traveled to access an account, from 4.8 to 1.3 kilometers. Additionally, the proportion of beneficiaries who walked to withdraw their transfer payment increased by 59 percent, allowing for beneficiaries not to forego housework, childcare, or work in order to access an account. Furthermore, beneficiaries who faced the largest reduction in indirect transaction costs, proxied by road distance, increased their financial activity (increased number of withdrawals and savings balance) the most. Ultimately, debit cards lower transaction costs by reducing the distance to access bank accounts and encourage account holders to transform their traditional method of transportation as well as banking in order not to forego important activities.

Also in Mexico, Higgins (2018) finds that when the Mexican government began providing debit cards to cash transfer recipients in urban areas, small retailers responded by adopting point of sale (POS) terminals to accept card payments. The number of POS terminals then increased in local areas by 18 percent relative to areas that had not been transformed. Similarly, consumers, too, responded to the increase in financial technology (fintech) adoption. Consumers who already shopped at corner stores adopted debit cards, and richer consumers who already had debit cards shifted 12 percent of their supermarket consumption to corner stores. Corner stores then benefited from the demand shock, as their profits increased due to an ability to turn over more inventory and increase both sales and merchandise costs by 3 percent while keeping other input costs fixed. The authors conclude that active government policy that spurs adoption on one side of the market can lead to dynamic, market-driven fintech adoption on both sides of the market, thus benefitting both consumers and retailers.

Jack and Suri (2014) test the importance of transaction costs as a barrier to access to finance by households in the context of the rapid expansion of M-Pesa, a mobile phone-based money transfer product in Kenya that was adopted by a large majority of households in less than 4 years. The authors present evidence that mobile money has a significant impact on the ability of households to share risk, which the authors argue is attributable to the associated reduction in transaction costs. The authors report that consumption of households that use M-Pesa is unaffected during a negative shock, whereas households who do not use the technology suffered a 7 percent drop. The authors further argue that consumption smoothing is enhanced by the adoption of mobile-money accounts because it provides access to remittances that are crucial during a negative shock. In fact, households who use M-Pesa received a greater number of remittances and larger amounts of money in total than households that did not. Moreover, households that use M-Pesa received remittances from further distances and from a larger sample of network members. This evidence emphasizes the importance of transaction costs when using social networks to smooth consumption. That is, the risk-sharing networks of these households were enlarged thanks to mobile money, as it effectively increases the size and number of active participants in a household's network without increasing any information, monitoring, and commitment costs.

Another paper by Jack and Suri (2016) studies how access to the Kenyan mobile money system (M-Pesa) increased per capita consumption levels while also lifting 2 percent of Kenyan households out of poverty. Interestingly, the effects, which are more pronounced for female headed households, appear to be driven by changes in financial behavior - in particular, increased financial resilience and occupational choices for the women who made the decision to move out of agriculture. Mobile money has therefore increased the efficiency of the allocation of consumption over time while allowing a more efficient allocation of labor, resulting in a reduction of poverty in Kenya.

In sum, there are notable contributions to the literature on how the advent of digital technologies affect local labor markets in Africa, and on how household welfare has been improved by the adoption of digital tools that reduce the costs of financial transactions. Yet, as mentioned above, there seems to be a blind spot in the literature when it comes to assessing the empirical relationship between unemployment and the digital economy. The following section describes the international and publicly available data we use to estimate the partial correlation between unemployment and the digital economy across countries.

III. Data

We first describe the data concerning the dependent variable, namely national unemployment rates. In turn, this section discusses the data concerning the explanatory variables including the proxies of the incidence of the digital economy and other controls used in the econometric estimations.

A. Dependent Variable: Unemployment Rates

The dependent variable is the average unemployment rate of a large sample of countries between the years 2000 and 2017. The time period is determined by our view of when digital technologies became commonplace; they were virtually non-existent in the twentieth century.

The unemployment rate is defined as the number of unemployed persons (years 15+) as a percentage of the total number of persons in the labor force (adults ages 15+). More specifically, the International Labor Organization (ILO) defines the unemployed as all persons of working age who are: 1) without work (neither paid employment nor self-employment) during a reference period; 2) available for work (either paid or self-employment); and 3) are seeking work by taking specific job-search actions in a specified period of time in pursuit of paid employment or self-employment.[2] This definition is useful for the ongoing because of its consideration of self-employment, which is commonly associated with "informal" employment in developing countries. The latter refers to employment without formal contracts and/or without social security (or retirement benefits provided by the state) coverage. Combined with low household savings and non-existent publicly provided unemployment benefits, which in turn imply that workers in many developing countries cannot survive without income flows, this feature of unemployment implies a negative correlation between informal employment and unemployment across developing economies.

The unemployment data were downloaded directly from the ILO's statistical database, ILOSTAT, which contains both nationally reported and imputed data.[3] This data set is also reported by the World Development Indicators of the World Bank, it is not always consistent with other sources of labor-market data, including official national estimates. To prevent contamination of the estimation sample by the ILO's imputation model, which could

[2] This definition comes from the ILO web site as of January 27, 2020. Please see https://ilostat.ilo.org/resources/methods/description-unemployment-rate/.
[3] The ILO utilizes a panel-data model that predicts unemployment with various national indicators of economic activity, such as GDP growth rates.

produce correlations by construction with macroeconomic variables, in this paper, we work only with the non-imputed ILO data. Table A1 in the Appendix contains the descriptive statistics of the resulting data sets, including for the unemployment variable.

B. Proxies for the Incidence of the Digital Economy

To study the correlation between the digital economy and unemployment, we rely on two alternative proxies for the incidence of the digital economy. The first, motivated by Hjort and Paulsen (2019), is internet users as a percentage of the population. It is defined as the proportion of individuals using the internet, based on results from national household surveys implemented by national authorities and then reported back to the United Nations. The survey questionnaires were designed by experts under the aegis of the United Nations. These international data are available for a large number of countries from the International Telecommunication Union (ITU), which is the relevant U.N. agency, and spans 2000 to 2017.[4] Since the empirics explore the relationship between the digital economy and frictional or long-term unemployment, we use country averages from 2000-2017 of the ITU indicator as the first proxy of the incidence of the digital economy.

The ITU variable is appealing for its cross-country and over-time coverage, but it might not be a good proxy for the incidence of the digital economy as it does not contain information about the purpose of the use of the internet, or whether it is used to conduct economic transactions. Consequently, we also use another proxy variable that concerns the use of the internet for economic transactions, and thus is consistent with the data used in Bachas et al (2018), Higgins (2018), and Jack and Suri (2014). It is the percentage of the adult

[4] The data were downloaded in June 2019 from https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx.

population (aged 15 or more) that used the internet to pay bills or make purchases during in the previous 12 months prior to the survey (conducted by Gallop in collaboration with the World Bank). The survey data aggregated at the national level were downloaded from the World Bank Global Findex Database, using the available data from the years 2014 and 2017.[5] The empirics use the average for countries with two data points and the single observation for countries with one data point.

C. Other Controls

To minimize omitted-variable bias (OVB) in the estimated partial correlation between unemployment and the proxies of the incidence of the digital economy, the econometric models discussed below include several control variables. As discussed further below, the evidence indicates that a key control variable is the informality rate.

Data on informality were downloaded from ILOSTAT, where it is defined as the percentage of people who, during a given reference period, were employed in at least one informal sector enterprise, irrespective of their status in employment and whether it was their primary or secondary job. Again, we work with long-term averages of informality computed with data from 2006-2018. It is worth noting that most high-income countries do not report informality, neither in the ILO database nor in their official labor-market statistics. As will become evident in the following section, this omission presents a key challenge for assessing the partial correlation between unemployment and the incidence of the digital economy. Consequently, we present results with and without imputing informality rates in high-income economies, which we set equal to zero in one set of estimations.

[5] The data were downloaded in June 2019 from https://globalfindex.worldbank.org/.

Since the objective is to assess the partial correlation between the digital economy and long-term or frictional unemployment, the econometric estimations also control for a correlate of the business cycle, namely the log difference between observed GDP and trend GDP. The GDP series are in local currency at constant prices and were downloaded from the World Bank's World Development Indicators database. In turn, we applied the Hodrik-Prescott filter to the log of GDP series from 1970-2017 on a country-by-country basis using the standard filtering window for annual data. Finally, we use the average log difference between the observed and trend GDP series from 2000-2017 as the proxy for the phase of each country's business cycle during the estimation sample period. Although the averaging of unemployment across 2000-2017 by itself should remove some of the cyclical component of unemployment, the sample period covers the years of the Global Financial Crisis and there is no guarantee ex-ante that average unemployment rates during this time period were unaffected by economic fluctuations associated with the global downturn as it spread across the world. Consequently, to err on the side of caution, the results section discusses results with and without controlling for the business cycle.

Another potentially important control concerns policy-induced labor market frictions. Specifically, we use an indicator of the costs of severance pay for dismissal, reported as a percentage of the average yearly salary. The underlying data are from 2015-2017 and were downloaded from the World Bank's Doing Business Database.[6] We work with country averages. The costs of employment separations, under certain wage-setting conditions, can be interpreted as de facto hiring costs. Indeed, there is a long-standing

[6] https://www.doingbusiness.org/

literature on how firing costs can affect unemployment, depending on labor supply and demand elasticities (see, e.g., Lyungquist 2002; Garibaldi and Violante 2005).

The fourth and final control in this study covers the ratio of private credit by deposit money to GDP, covering the years 2000 through 2016 and downloaded from the Financial Development and Structure Database. This control helps identify the partial correlation between unemployment and the incidence of the digital economy when the proxy for the latter is the share of the adult population that reports paying bills over the internet. In fact, as shown in the Appendix tables, in most of our estimation samples there is a positive correlation between internet payments and bank credit.

D. Instrumental Variables

As discussed further below, to further assess the partial correlation of interest, we also estimate a series of IV models. These models use two additional variables as instruments, with their validity and power assessed in the results section. One is the number of fixed telephone lines per capita averaged over a pre-sample historical period, 1975-1999. The conjecture is that countries that had laid out the infrastructure for fixed-line telephony in the late 20th century are also countries with a high coverage of internet use and potentially of digital payments. Since unemployment during 2000-17 is unlikely to have caused fixed-line coverage during 1975-99, it might be a suitable IV. In addition, we explore IV-estimations with dummy variables that identify the legal origin of each country. These variables appear as IVs in articles that study the relationship between financial development and economic growth. The seminal article in this vein is Levine, Loayza, and Beck (2000). The set of dummy variables includes British, French, German and Scandinavian legal origins. Lastly, given the results of the OLS estimations discussed below, which show that bank credit (as a share of GDP) is not a significant determinant of unemployment but is correlated with our proxies of the incidence of the digital economy, this variable is a good candidate for an IV. Again, the statistical appendix provides summary statistics for the data sets used in the IV estimations.

IV. Empirical Strategy and Results

To ascertain the potential functional form of the relationship between unemployment and the digital economy, the empirical strategy builds from non-parametric estimations of the relationship between unemployment and internet use, which is the digital-economy proxy with the widest coverage. In turn, we present a series OLS estimates that explore quadratic and linear relationships of the unconditional correlation and conditional partial correlations. Finally, we turn our attention to IV estimates of the partial correlation of interest.

A. Non-parametric estimations

Figure 1 shows the results from non-parametric estimations of the relationship between the two proxies of the digital economy (internet users and digital payments) and unemployment rates across countries. In both cases, the data seem to follow an inverted-u shape function. Unemployment tends to rise initially up to a point when the slope turns negative. The upward sloping portion of the curve seems to be associated with developing countries, which are coded in blue whereas high-income economies are coded in green. Indeed, Figures 2 and 3 show that when the sample of countries is limited to high-income economies, the relationship appears to be strictly negative, whereas the relationship is strictly positive for developing countries. Hence the question arises: Is there an omitted variable that is particularly important for developing economies that creates an upward bias in the correlation between the proxies of the digital economy and unemployment?

Figure 1: Unemployment and the Digital Economy: Non-Parametric Estimations

All countries

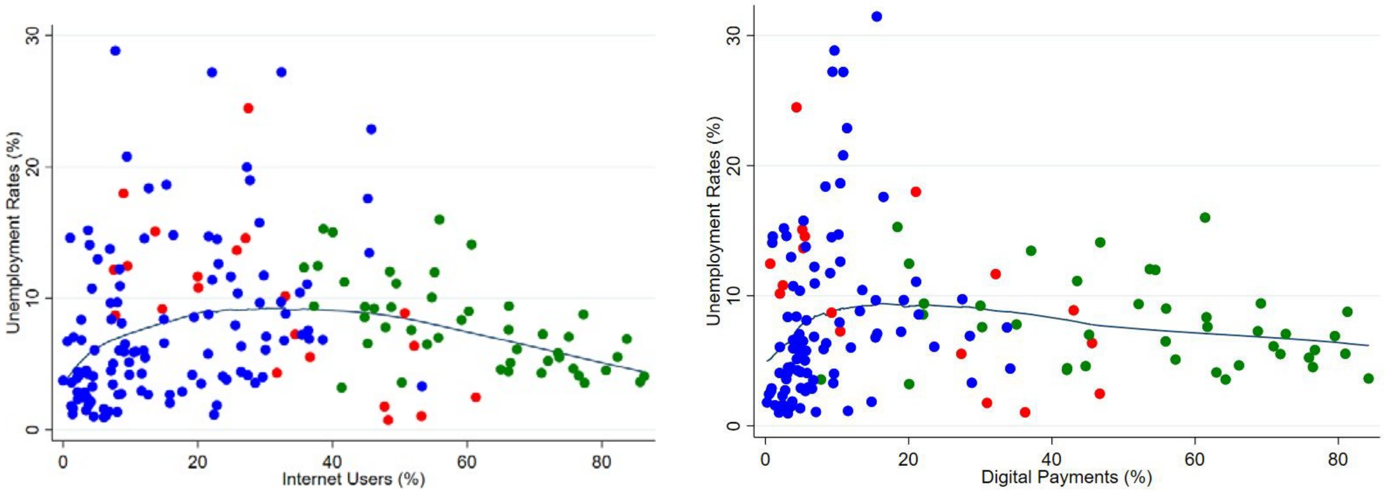


Figure 2: High-Income Countries

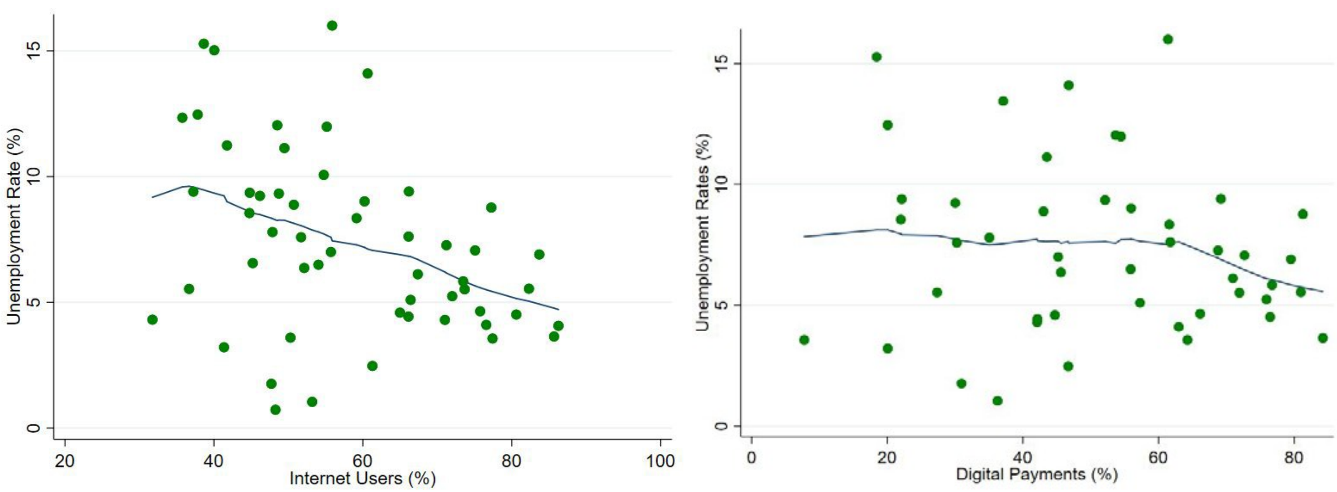
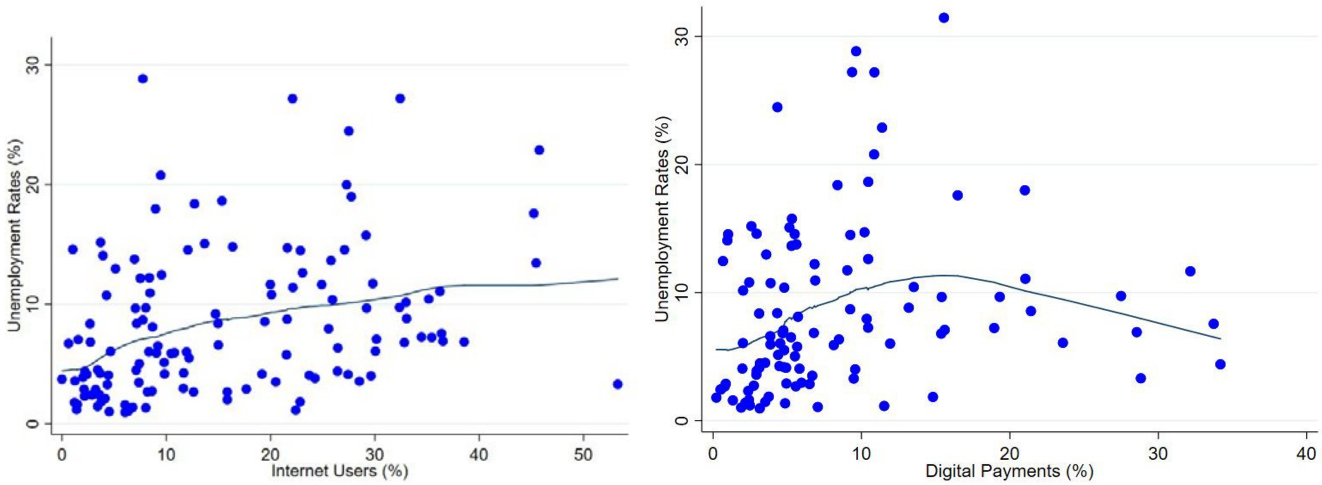


Figure 3: Non-High-Income Countries



Source: World Bank Data Bank & Global Findex Database. "Internet Users" = internet users (% of adults 15+). "Digital Payments" = Individuals that used internet to make payments in the past year (% of adults 15+). Please see Appendix for the variable definitions and sources.

B. Bi-variate Correlations and Omitted Variable Bias (OVB)

The easiest way to think about OVB is in a three-variable model, where $y = a*X_1 + b*X_2$. The bias would come from estimating the model only with variable X_1. The textbook Omitted Variable Formula (OVF) can be written as: $E\ [a|X_1] = a + p*b$, where $p = corr\ (X_1, X_2)$ and $b = corr\ (y, X_2)$.[7] Simply put, the bias in the bi-variate correlation caused by the omission of a relevant variable is equal to the product of two correlations, the correlation between the omitted variable and the variable of interest and the correlation between the omitted variable and the dependent variable.

In the ongoing application, we suspect that there is OVB in the bi-variate correlation between unemployment and the digital economy proxies due to an omitted variable that is particularly important for developing economies. A good candidate is informal employment, which is ubiquitous in developing countries but not in high-income economies.

[7] For example, see Greene (2003, p. 148).

Appendix Table A3, Panel A, reports a positive correlation between unemployment and internet usage of 0.02. However, the correlation between informality and internet use is - 0.82, and the correlation between informality and unemployment is -0.59. The latter reflects the fact that poor people in developing countries cannot afford to be unemployed, which is defined as the condition of actively looking for a job while not having a source of income. Hence, based on this set of bi-variate correlations, we can compute the OVB in the bi-variate relationship between internet use and unemployment due to the omission of informality: OVB = *-0.82 * -0.59 = 0.48*. That is, the omission of informality produces an upward bias in the correlation between unemployment and internet use that is much larger than the observed bi-variate correlation between unemployment and internet use, and correlation conditional on informality is about -0.46. For the case of digital payments, the upward bias is: OMV = -0.73 * -0.59 = 0.43. Since the observed correlation between unemployment and digital payments is -0.06, we expect the partial correlation after controlling for informality to be about -0.50, which is statistically indistinguishable from -0.46, the conditional correlation between unemployment and internet use. It is an empirical question whether internet use or digital payments remain negatively correlated with unemployment once we control for both proxies of the digital economy. The following section revisits the issues of the functional form and OVB by presenting econometric estimates of the partial correlation coefficients between unemployment and the two proxies of the digital economy.

C. OLS Results

Table 1 reports our baseline OLS estimates of the partial correlation between unemployment and the digital economy across countries. Panel A presents the results for estimations that utilize the maximum sample of countries possible but also compares some specifications across common samples. Panel B presents the results from estimations that use the maximum sample of countries after imputing informality for high-income countries that do not report informality by setting the informality rate for those countries equal to zero. Panel C presents results for a small common sample of 59 developing countries. The main objective of this set of results is to determine whether the inverted-u shape function is a figment of OVB, and in turn, to assess the "true" partial correlation between unemployment on the one hand, and internet coverage and digital payments on the other hand, after controlling for informality and the other variables that might be correlated with unemployment.

In Columns 1 and 5 of Panels A and B, we report results with the maximum available sample, running a regression only with our free-standing digital payments and internet coverage variables and their quadratic terms. In both cases, the coefficients for the freestanding variables are positive and statistically significant, and their quadratic terms are negative and also statistically significant. These results confirm what we already knewfrom the non-parametric estimations: there is an inverted-u relationship between unemployment and the two proxies of the digital economy. However, in Columns 1 and 5 of Panel C, the quadratic function is not significant, because the sample of countries is limited to developing economies.

Next, in Columns 2 and 6 of Panel A, we restrict the regressions to a smaller sample, using the set of countries that have data on informality, thus reducing the sample size from 151 to 61 in Column 2 and from 182 to 66 in Column 6. These smaller samples are limited to developing countries and emerging markets that report informality rates. The main finding from these two specifications is that the quadratic functional form loses significance; the quadratic terms are not statistically significant, but the free-standing term is positive and statistically significant for both proxies of the digital economy. This finding confirms what we saw in the non-parametric estimations, where the relationship appears to be positive for developing economies, probably due to the OVB. In contrast, the results under Columns 2 and 6 of Panel B, which utilize data from high-income countries as well as developing economies, show that the quadratic functional form remains significant.

Columns 3 and 7 in Panels A and B control for informality. In both panels, informality appears with a statistically significant negative coefficient, reflecting the negative correlations between unemployment and informality discussed above. In Panel A, with the smaller sample of developing and emerging economies, controlling for informality does not bring back the quadratic functional form. In Panel B, with the larger sample that includes high income economies with imputed informality, the inclusion of informality in Columns 3 and 7 flips the signs on the free-standing and quadratic terms of the digital economy variables.

Under columns 4 and 8, the results in Panels A and B indicate that the free-standing digital-economy variables have a negative sign, but it is not significant in the case of internet use in the sample of developing countries under Panel A. Both are significant and negative with the larger sample under Panel B.

Columns 9-11 under Panels A and B present the results after the inclusion of additional controls. Column 9 includes two controls, namely the output gap and severance pay. Column 10 adds bank credit, which helps identify the partial correlation between unemployment and digital payments, since the latter is positively correlated with bank credit. Column 11 includes all the controls mentioned above plus both proxies of the digital economy. The results under both panels are qualitatively similar but with notable differences in the magnitude of the coefficients. The inclusion of the output gap and severance yields similar point estimates of the coefficient on digital payments of -0.297 in Panel A and -0.206 in Panel B with the extended sample. Under column 10, the previous results hold after adding bank credit, with the coefficient on digital payments being -0.289 in Panel A and -0.193 in Panel B. However, in Column 11, which includes both digital payments and internet use, the results indicate that digital payments remain negative and statistically significant whereas the internet-use variable becomes statistically insignificant under both Panels A and B. It is also noteworthy that the partial correlation coefficient under Panel A of -0.403 is more than twice as big as the estimate under Panel B of -0.152, which utilizes the larger sample that includes high-income economies.

Panel C presents a set of estimations that use a constant sample that allows for comparisons of coefficient estimates across specifications. This comes at the expense of losing a substantial number of observations. However, the sample is the same that was reported under Column 11 in Panel A. The results confirm that in the sample that includes only developing countries, the quadratic functional form specification is not significant, as shown in Columns 1, 2, 4 and 6. The partial correlation coefficient on digital payments is significant across specifications 3, 7, 8 and 9, the latter being identical to the specification reported under Column 11 in Panel A. Also, the set of results with the common sample suggests that internet use is not statistically significant while the digital-payments variable is, thus suggesting that the previous results were not due to changes in samples.

In sum, it appears that the digital payments variable is a better proxy for the incidence of the digital economy than internet use. Its OLS partial correlation coefficient is robustly negative and significant after controlling for informality, regardless of the estimation samples and the inclusion of additional controls. However, with the smaller samples of developing countries, the estimated partial correlation coefficients seem to be larger than when estimated with the larger sample that includes high-income countries (with imputed informality rates). It remains an open question whether the OLS estimates of the partial correlation coefficients reflect endogeneity, whereby economies with high unemployment rates tend to have lower digital payments than economies with low unemployment, after controlling for informality.

D. IV Results

To further explore the partial correlation coefficients between unemployment and proxies of the digital economy, Table 2 presents results from Two-Stage Least Squares (TSLS) estimations. We present three alternative specifications with our two proxies for the digital economy treated as endogenous variables. Panel A presents the second-stage unemployment equation results; Panel B presents the first-stage results. The specifications under Columns 1 and 2 are just identified; the number of IVs equals the number of endogenous variables. Column 3 presents the results from an over-identified specification.

Specifications 1 and 2 use the average fixed telephone lines per capita (in logs) during 1975-99 as an IV. Presumably this variable would be a good IV for internet access and possibly for digital payments, which require access to the internet. As mentioned in the data section above, the expectation is that countries that had high coverage of telephone infrastructure in the decades prior to the 21st century were more likely to have extensive coverage of the internet thereafter. In fact, it is well known that the physical infrastructure used to offer fixed-line telephony was used to place the fiber-optic cables that brought broadband internet (Geere, 2011). Indeed, APEC (2013) explains that modern undersea cables that carry fiber optic cables are a direct descendant of telegraph cables from 150 years ago.

The other IV in specifications 1 and 2 is bank credit, the same variable that was presented in the OLS specifications as an additional control variable. It is a potentially valid IV because it is correlated with digital payments but has a low correlation with unemployment -- see Appendix Table A3. In fact, although the relevant coefficient was not reported, the results from the specifications reported in Table 1 indicate that bank credit is not directly correlated with unemployment, regardless of the estimation sample. Specification 3 in Table 3 is over-identified, as it includes the four legal origin dummy variables in addition to the bank credit and historical telephone lines.

Panel C in Table 2 reports well known specification tests. The first is a test of exogeneity. The null is that the digital-economy variables are exogenous. The Durbin (1954) test measures the correlation between the residuals of the OLS model estimated under the assumption that the digital-economy variables are exogenous and the IV model that assumes that they are endogenous. If the residuals from both models are correlated, then the variables are thought to be exogenous. We report the probability value of the Durbin test, with low values indicating that the null of exogeneity is rejected. Alternative exogeneity tests can be computed. In our case, the results from a similar Wu-Hausman test, which can accommodate heteroskedasticity in the residuals, give similarly low p-values.[8] Hence it seems that it is appropriate to assume that the digital economy variables are endogenous from a statistical point of view.

[8] For the sake of brevity, results of the Wu-Hausman test are available upon request. See Hausman (1978).

The second specification test is a classic and simple test of weak IVs. Weak IVs are those that might be significant determinants of the endogenous explanatory variables but that nevertheless explain a small share of the variation of the endogenous variables. The Shea (1997) test is simple: we report the partial R-squared of the first stage regression. It provides a measure of the variation of the endogenous variables that is explained by the IVs. Although there are no critical values for this test, a rule-of-thumb in the literature is that it should be above 10%. In our case, the identification of the exogenous variation of digital payments is rather weak in specifications 1 and 2 but strong, at 16%, in specification 3, which includes the additional IVs in the form of the legal-origin dummy variables. The identification of the exogenous variation of the internet-users variable appears strong across the three specifications.

The third specification test is Sargan's (1958) test of overidentification. It is a test of the null hypothesis that the correlation between the IVs and the errors is zero. A high p-value indicates that the IVs are valid. This test can only be applied to overidentified models, such as our specification 3, because it tests the correlation between the IVs and the errors one at a time. The specification under column 3 appears to be using valid IVs that satisfy the exclusion restriction. Alternative estimation methods and specification tests not reported here yielded similar results. [9]

The first notable set of results concerns the coefficient estimate on the digital-payments variable. It appears with negative and statistically significant coefficients in Panel

[9] Similar results were obtained for Hansen's test of over-identification. Specification tests with robust standard errors adjusted for small-sample properties yield similar results: there is evidence of weak IV for digital payments, but not for internet use. Also, the p-value of the T-statistics reported in Panel A of Table 2 are lower than those reported herein when with the robust small-sample adjustment. LIML estimations, instead of 2SLS estimates, yielded virtually identical point estimates but with higher precision. That is, Table 2 reports the most conservative estimates of the relevant specification tests.

A. However, the magnitude of the coefficient drops substantially in specification 3, which is also the model that seems to have stronger IVs. Yet, even in this specification the coefficient estimate has an absolute value that is almost twice as big as the OLS estimate presented in Table 1, Panel B, which uses a similar sample of countries (including high-income economies with imputed informality). In table 1, Panel B, column 11 the estimate was -0.15, whereas the IV estimate in in Table 2, model 3 the coefficient is -0.27. The latter implies that a one percentage point increase in the incidence of digital payments over the adult population of a country is associated with a decline of 0.27 percentage points in the long-term frictional unemployment rate (since we are controlling for business cycle fluctuations). In contrast, the estimated partial correlation coefficient on the internet-use variable appears with a positive sign, although it is not statistically significant in our preferred IV model 3.

V. Conclusions

This paper aimed to explore the correlation between unemployment and the incidence of the digital economy across countries. Although the digital technologies presumably help alleviate search-and-matching frictions in labor markets, there is surprisingly little written about this potential correlation. The most directly related literature had found that the advent of high-speed internet in Africa was associated with improvement in employment rates in local labor markets. But the existing literature has not explored the link with unemployment per se.

The unconditional correlation between unemployment rates and our two proxies of the digital economy – namely digital payments and internet use – appears to follow an inverted-U shape or quadratic function. This is true with non-parametric as well as parametric estimations. However, the bi-variate correlations in the data revealed that there is potentially an important source of OVB affecting the partial correlation between unemployment and the digital economy variables among developing countries. Simple computations suggest that omission of labor market informality creates a substantial upward bias in the correlation between unemployment and the proxies of the digital economy.

After controlling for informality, as well as other controls, the OLS partial correlation between unemployment and the incidence of digital payments turns robustly negative and statistically significant. Moreover, the magnitude of the OLS coefficient seems to be larger in absolute value for samples of developing countries than for samples that include high-income economies. However, the latter required using imputed values for informality, because high-income economies do not report informal employment rates. Our best guess is that the OLS partial correlation falls somewhere between -0.15 and -0.40.

We further studied the partial correlation coefficient between unemployment and the digital economy in an IV-2SLS framework. The evidence suggests that the digital economy variables are probably endogenous from a purely statistical point of view. Our IV estimates for the digital-payments variables range from -0.55 to -0.27, with the latter estimate coming from the best specified IV model with the strongest set of IVs. The set of IVs that appeared to work best were motivated by the existing literature on finance and growth, complimented with historical indicators of the coverage of fixed-line telephony. Consequently, we are tempted to conclude that the true partial correlation between unemployment and the incidence of digital payments across countries is probably in the range of -0.15 (our lowest OLS estimate) and -0.27 (our lowest IV estimate).

The evidence presented herein also seems to indicate that digital payments are probably a better proxy for the incidence of the digital economy than internet use. One could argue, for example, that internet use is like using televisions for entertainment. If anything, we found positive partial correlations between unemployment and internet use, although in most OLS and IV specifications the estimated partial coefficient was not statistically significant. Nonetheless, we hesitate to draw strong conclusions about causality, because our IVs are imperfect, with the seemingly stronger set of IVs yielding the more modest negative partial correlation coefficient between unemployment and the incidence of digital payments.

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Table 1. OLS Estimates of the Partial Correlation between Unemployment and the Digital Economy across Countries

Panel A: Full Sample											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Payments	0.138**	1.024*	-0.066	-0.338*					-0.297*	-0.289*	-0.403**
Payments (^2)	-0.002***	-0.028	-0.013								
Users (%)					0.251***	0.487**	0.144	-0.072			0.054
Users (%) (^2)					-0.003***	-0.007	-0.005				
Informality (%)			-0.262***	-0.266***			-0.201***	-0.206***	-0.254***	-0.255***	-0.221***
Other controls	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES
Bank credit (%)	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Observations	151	61	61	61	182	66	66	66	60	60	59
Panel B: Sample with Informality Imputed for High Income (=0 for all high-income countries without reported informality)											
Payments	0.138**	0.288***	-0.496***	-0.219***					-0.206***	-.193***	-0.152**
Payments (^2)	-0.002***	-0.004***	0.003**								
Users (%)					0.251***	0.387***	0.083	-0.215***			-0.030
Users (%) (^2)					-0.003*	-0.005***	-0.003*				
Informality (%)			-0.245***	-0.194***			-0.133***	-0.194***	-0.187***	-0.190***	-0.180***
Other controls	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES
Bank credit (%)	NO	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES
Observations	151	93	93	93	182	99	99	99	92	92	91
Panel C: Smallest Common Sample											
Payments	0.884	-0.139	-0.405**				-0.366**	-0.358**	-0.403**		
Payments (^2)	-0.0267	-0.013									
Users (%)				0.485**	0.114	-0.066			0.054		
Users (%) (^2)				-0.006	-0.004						
Informality (%)		-0.249***	-0.252***		-0.211***	-0.215***	-0.237***	-0.238***	-0.221***		
Other controls	NO	NO	NO	NO	NO	NO	YES	YES	YES		
Bank credit (%)	NO	NO	NO	NO	NO	NO	NO	YES	YES		
Observations	59	59	59	59	59	59	59	59	59		

Source: Authors' calculations based on data from ILOSTAT, Global Findex Database, and the World Development Indicators. Notes: * p<0.10; ** p<0.05; *** p<0.01. The table reports OLS estimates. "Payments" refers to the share of adult population that reports having made a payment over the internet. "Users" refers to the share of the population with access to the internet. "Other controls" include the following variables: a. GDP % deviation from trend, and b. severance pay of redundancy dismissal (% of annual salary). Bank credit is private bank credit to GDP (%) and it is not statistically significant in any specification. See Appendix for sources and definitions.

Table 2: Two Stage Least Squares Estimates of the Partial Correlation between Unemployment and the Digital Economy across Countries

	(1)		(2)		(3)	
Explanatory Variables	**Panel A - IV Estimates: Dependent Variable - Unemployment**					
Payments	-0.464		-0.553		-0.268	
	(0.06)		(0.073)		(0.068)	
Users	0.308		0.399		0.248	
	(0.111)		(0.082)		(0.127)	
	Panel B - First Stage: Dependent Variables					
	Payments	Users	Payments	Users	Payments	Users
Telephones 75-99 (log)	1.423	5.134	2.258	5.906	2.163	5.652
	(0.415)	(0.000)	(0.224)	(0.000)	(0.236)	(0.000)
Bank credit 2000-16 (% of GDP)	0.0875	0.0557	0.077	0.046	0.064	0.043
	(0.012)	(0.022)	(0.027)	(0.058)	(0.053)	(0.060)
Legal Origin Dummy Variables	No		No		Yes	
	Panel C - Specification Tests					
H0: Exogeneity. p-value of Durbin Test	0.030		0.010		0.009	
Weak IVs: Shea's partial R-sq	0.071	0.200	0.050	0.170	0.159	0.227
IV Validity: Sargan Overid Test p-value	n.a.		n.a.		0.666	
Other controls *	Informality, Output Gap		Informality, Output Gap, Severance		Informality, Output Gap, Severance	
Observations	100		99		97	

Source: Authors' calculations. **Notes**: See text and appendix for data sources and variable definitions. "Users" = internet users (% of adults 15+). "Payments" = Used internet to make payments (% of adults 15+). "Telephones 75-99 (log)" = log of average number of fixed telephone lines per capita, 1975-1999. "Bank credit" = Bank credit to the private sector (% of GDP). "Informality" = share of informal employment. "Output Gap" = log difference between observed GDP and trend GDP. "Severance" = severance costs % of annual wage. P-values are reported within parentheses in Panels A and B. "n.a." = Not applicable. * Informality is not statistically significant in any of these specifications as a regressor of in the unemployment equation but it has a negative sign. The output gap is negative and significant only in specification 3. Severance is not significant in any specification.

Data Appendix

Table A1. List of Variables, Definitions and Sources

Variables	Description	Source
Dependent Variable	National unemployment rates: the average unemployment rates of MENA countries between years 2000 and 2017, defined as the number of unemployed persons (aged 15 and over) as a percentage of the total number of persons in the labor force	International Labor Organization Department of Statistics; https://www.ilo.org/ilostat\
Digital Economy Variables	Internet users: the average proportion of individuals using the Internet based on results from national household surveys spanning 2000 to 2017	International Telecommunication Union; https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx
	Internet payments: percentage of population aged 15 or more that used the Internet to pay bills or buy online in the past 12 months, using data from 2011, 2014, and 2017. For countries with more than one data point, we use the average.	World Bank Global Findex Database; https://globalfindex.worldbank.org/
Informality in non-agricultural sectors	Informal employment: the percentage of people who, during a given reference period, were employed in at least one informal sector enterprise, irrespective of their status in employment and whether it was their primary or secondary job; the data spans 2006 through 2018 but without the inclusion of High-Income countries	International Labor Organization Department of Statistics; https://www.ilo.org/ilostat\
Other controls	GDP deviation from trend: reported in constant local currency using the Hodrick Prescott filter and was obtained via staff calculations. The original data used in these calculations can be found at the World Development Indicators database, covering 2000 through 2017.	World Development Indicators; https://datacatalog.worldbank.org/dataset/world-development-indicators
	Account severance pay for dismissal: reported as a percentage of one's yearly salary which covers 2015, 2016, 2017, 2018, 2019.	Doing Business Database; https://www.doingbusiness.org/
	Bank Credit: Ratio of private credit by deposit money to GDP, covering the years 2000 through 2016	Financial Development and Structure Database; https://www.worldbank.org/en/publication/gfdr/data/financial-structure-database
Instrumental Variables	Telephone subscriptions 75-99: the log of average number of fixed telephone lines per capita, 1975-1999	International Telecommunication Union; https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx
	Bank Credit: Ratio of private credit by deposit money to GDP, covering the years 2000 through 2016	Financial Development and Structure Database; https://www.worldbank.org/en/publication/gfdr/data/financial-structure-database

Table A2. Descriptive Statistics

Panel A. Maximum Sample

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Unemployment	185	8.19	5.85	0.73	31.46
Internet payments	151	21.39	23.48	0.222	84.23
Internet users	199	29.31	23.59	0	86.28
Informality	68	64.78	20.92	15.07	99.01
GDP deviation from trend	203	-15.1	64.94	-457.09	308.82
Severance pay	178	6.72	8.21	0	50
Bank Credit	182	45.83	41.52	1.23	285.7
Log (Fixed Telephone)	207	1.495	1.807	-2.801	4.315

Panel B. Sample Used in Column 11 of Table 1 Panel A

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Unemployment	59	7.32	6.34	0.96	27.22
Internet payments	59	6.58	5.03	0.22	22.13
Internet users	59	14.99	12.01	1.2	45.23
Informality	59	66.52	21.18	15.07	99.01
GDP deviation from trend	59	-16.09	19.21	-85.18	15.79
Severance pay	59	8.68	7.54	0	33.33
Bank Credit	59	30.72	38.2	2.7	285.7

Panel C. Sample used in Column 11 of Table 1 Panel B

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Unemployment	91	7.51	5.45	0.96	27.22
Internet payments	91	25.32	27.61	0.222	84.23
Internet users	91	32.5	26.85	1.2	85.68
Informality	91	43.13	36.18	0	99.01
GDP deviation from trend	91	-11.68	18.25	-85.18	15.79
Severance pay	91	6.89	7.24	0	33.33
Bank Credit	91	51.47	46.57	2.69	285.7

Panel D. Sample used in Column 9 of Table 1 Panel C

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Unemployment	59	7.32	6.34	0.96	27.22
Internet payments	59	6.58	5.03	0.22	22.13
Internet users	59	14.99	12.01	1.2	45.23
Informality	59	66.52	21.18	15.07	99.01
GDP deviation from trend	59	-16.09	19.21	-85.18	15.79
Severance pay	59	8.68	7.54	0	33.33
Bank Credit	59	30.72	38.2	2.7	285.7

Panel E. Sample Used in Column 3 of Table 2

Variable	Observations	Mean	Std. Dev.	Min.	Max.
Unemployment	97	7.081	4.99	0.960	27.22
Internet payments	97	26.96	26.86	0 .22	84.23
Internet users	97	34.56	26.54	1.20	85.68
Log (Fixed Telephones)	97	1.48	1.99	-2.41	4.14
Bank Credit	97	55.72	48.46	5.92	285.70
Legal Origin UK	97	0.30	0.46	0	1
Legal Origin France	97	0.49	0.50	0	1
Legal Origin German	97	0.15	0.36	0	1
Legal Origin Scandinavian	97	0.04	0.20	0	1

Table A3. Bi-variate Correlation Matrices

Panel A. Maximum Sample

Entire Dataset	Unemployment	Internet payments	Internet users	Informality	GDP deviation	Severance pay	Bank Credit	Telephone subscriptions 75-99
Unemployment	1.000							
Internet payments	-0.057	1.000						
Internet users	0.022	0.919	1.000					
Informality	-0.593	-0.726	-0.819	1.000				
GDP deviation	-0.082	0.149	0.154	0.12	1.000			
Severance pay	-0.082	-0.274	-0.273	0.052	-0.016	1.000		
Bank Credit	-0.085	0.625	0.661	-0.127	0.147	-0.243	1.000	
Log (Telephone subscriptions 75-99)	0.188	0.766	0.854	-0.836	0.110	-0.191	0.582	1.000

Panel B. Sample used in Column 11 of Table 1 Panel A (59 observations)

Original Sample	Unemployment	Internet payments	Internet users	Informality	GDP deviation	Severance pay	Bank Credit
Unemployment	1.000						
Internet payments	0.279	1.000					
Internet users	0.466	0.765	1.000				
Informality	-0.615	-0.711	0.466	1.000			
GDP deviation	-0.293	-0.096	-0.108	0.177	1.000		
Severance pay	-0.154	0.088	0.075	-0.017	0.054	1.000	
Bank Credit	0.018	0.134	0.118	-0.136	-0.146	0.017	1.000

Panel C. Sample used in Column 11 of Table 1 Panel B (91 observations)

Full sample	Unemployment	Internet payments	Internet users	Informality	GDP deviation	Severance pay	Bank Credit
Unemployment	1.000						
Internet payments	0.020	1.000					
Internet users	0.128	0.947	1.000				
Informality	-0.312	-0.867	-0.925	1.000			
GDP deviation	-0.293	0.334	0.305	-0.221	1.000		
Severance pay	-0.069	-0.364	-0.341	0.290	-0.159	1.000	
Bank Credit	-0.014	0.634	0.628	-0.579	0.212	-0.269	1.000

Panel D. Sample used in Column 11 of Table 1 Panel C (59 observations)

Small sample	Unemployment	Internet payments	Internet users	Informality	GDP deviation	Severance pay	Bank Credit
Unemployment	1.000						
Internet payments	0.279	1.000					
Internet users	0.466	0.765	1.000				
Informality	-0.615	-0.711	-0.824	1.000			
GDP deviation	-0.293	-0.096	-0.108	0.177	1.000		
Severance pay	-0.154	0.088	0.075	-0.017	0.054	1.000	
Bank Credit	0.018	0.134	0.118	-0.136	-0.146	0.017	1.000

Panel E. Sample used in IV Estimation Column 3 of Table 2 (97 observations)

Entire Sample	Unemployment	Digital Payments	Internet Users	Log (fixed telephone)	Bank Credit	Legal origin UK	Legal origin France	Legal Origin German	Legal Origin Scandinavian
Unemployment	1.000								
Digital Payments	-0.0572	1.000							
Internet Users	0.022	0.9186	1.000						
Log (fixed telephone)	0.1884	0.7657	0.854	1.000					
Bank Credit	-0.0853	0.6246	0.661	0.582	1.000				
Legal origin UK	0.0058	0.0248	-0.010	-0.002	0.142	1.000			
Legal origin France	-0.0151	-0.3798	-0.291	-0.218	-0.313	-0.734	1.000		
Legal Origin German	0.0871	0.336	0.319	0.265	0.149	-0.245	-0.368	1.000	
Legal Origin Scandinavian	-0.0657	0.4234	0.387	0.239	0.291	-0.117	-0.176	-0.059	1.000