GÁBOR LOVICS

KATALIN SZŐKE

CSABA G. TÓTH

BÁLINT VÁN

THE EFFECT OF THE INTRODUCTION OF ONLINE CASH REGISTERS ON REPORTED TURNOVER IN HUNGARY

MNB OCCASIONAL PAPERS | 137

2019
DECEMBER

THE EFFECT OF THE INTRODUCTION OF ONLINE CASH REGISTERS ON REPORTED TURNOVER IN HUNGARY

MNB OCCASIONAL PAPERS | 137

2019

DECEMBER

MNB Occasional Papers 137

The effect of the introduction of online cash registers on reported turnover in Hungary*

(Az online pénztárgépek bevezetésének hatása a bejelentett forgalomra Magyarországon)

Written by Gábor Lovics, Katalin Szőke, Csaba G. Tóth, Bálint Ván**

Budapest, December 2019

Published by the Magyar Nemzeti Bank

Publisher in charge: Eszter Hergár

H-1054 Budapest, Szabadság tér 9.

www.mnb.hu

ISSN 1585-5678 (online)

* We are grateful to Ádám Reiff and Mária Pécs for their strong support, and also indebted to Danila Pankov for his valuable comments. Furthermore, a special note of thanks goes to Gergely Baksay, Gábor P. Kiss, Péter Tóth, Benedek Nobilis and Zoltán Vereczkei. We are also grateful for the comments we received at the 15th Conference of Economic Modeling and at the workshop of the Central Bank of Hungary.

** Gábor Lovics, Hungarian Central Statistical Office (gabor.lovics@ksh.hu);
Katalin Szőke, Central Bank of Hungary (szokek@mnb.hu);
Csaba G. Tóth, Hungarian Demographic Research Institute (toth@demografia.hu). The research was conducted while he was employed by Central Bank of Hungary;
Bálint Ván, Ministry of Finance (balint.van@pm.gov.hu).

Contents

Abstract

In order to reduce the shadow economy, in 2013 and 2014 the Hungarian government introduced mandatory online cash registers (OCR) in some sectors. As a result, almost 200,000 OCRs have been installed by 100,000 enterprises. In this paper we use micro data to estimate the effect of OCR introduction on reported turnover in the most affected sectors: retail, and accommodation and food services (AFS). We assume that OCR installation does not change a company's operating model, so the increase in reported turnover around the installation date reflects a reduction in the shadow economy. We identify a remarkable effect of OCR introduction on reported turnover in both sectors. For small enterprises, reported turnover increased by 23 percent and 35.1 percent in the retail and AFS sector, respectively. We also find significant but smaller effects for medium-sized enterprises in both sectors. For large companies, we only observe a significant impact in the AFS sector.

Keywords: Value Added Tax, Tax Evasion, Shadow Economy

JEL Codes: E26, H25, H26

Összefoglaló

A gazdaság fehérítésének érdekében a magyar kormány egyes ágazatokban kötelezővé tette az online pénztárgépek (OPG-k) bekötését 2013 és 2014 között. Az intézkedés eredményeképpen nagyjából 100 ezer cég közel 200 ezer online pénztárgépet helyezett üzembe. Tanulmányunkban az OPG-k bevezetésének a hatását vizsgáltuk a bejelentett forgalomra vállalati szintű adatbázis segítségével a leginkább érintett két szektorban: a kiskereskedelemben, illetve a vendéglátóiparban (szálláshely-szolgálatás és vendéglátás). Mivel az OPG-k bevezetése a vállalkozások valódi működését feltehetően nem befolyásolta, csupán a bejelentési gyakorlatukat, így az online pénztárgép(ek) üzembe helyezéséhez köthető forgalomnövekmény a szürke, illetve feketegazdaság visszaszorításának tekinthető. Számításaink szerint az online pénztárgépek bevezetése növelte a bejelentett forgalmat, azaz érdemi fehéredést eredményezett mindkét ágazatban. A bejelentett forgalom a kis cégek esetében a kiskereskedelemben 23 százalékkal, míg a vendéglátóipari szektorban 35,1 százalékkal emelkedett. Jelentős, de alacsonyabb hatást találtunk mindkét szektorban a közepes méretű cégek esetében, míg a nagyobb cégeknél csak a vendéglátóipari szektorban volt szignifikáns hatás.

Introduction

Since computers, cell phones, credit cards and many other devices now generate far more data on our habits and activities than ever before, the current period can be easily called the age of big data (Mayer – Cukier, 2013). One aspect of this information revolution is that authorities have a wealth of new data sources to collect information on people, enterprises and all other market participants. The use of new technologies and the resulting new data sources can change the behaviour of market participants and promote their compliance behaviour, and thus may lead to efficiency increases in several ways. Nevertheless, we still have limited knowledge about their real effect.

EFD (Electronic Fiscal Device) is a term used for a wide variety of technological devices which can help tax authorities monitor business transactions. The origins of EFDs date back to the 19th century, when the "Incorruptible Cashier" was invented by James Ritty in 1879 (Varian, 2010). This register had a display to indicate the amount of sale and a bell to ring up sales. Later, this machine was improved with a paper roll, to record sales transactions. The first electric cash register was developed in 1906, which used an electric motor. The first real EFDs were introduced in Italy in 1983. They were followed by the Greek tax administration, which introduced their own EFDs in 1988 (OECD, 2013).

Before 2000, some Eastern European countries such as Romania and Bulgaria also introduced similar devices. They were followed by Latin American countries such as Argentina and Brazil in the mid-1990s. Eastern African countries also continued this trend: Kenya, Tanzania and Ethiopia introduced EFDs in 2005 and 2010. In parallel with them, South Korea implemented these devices in 2005 as the first Asian country to use this technology (OECD, 2013; Eilu, 2018). While EFDs spread in the world they also became more and more advanced. They could record more data, and some of them could connect and send information to the national tax authority. Data was also sent more and more often via ever improving communication channels.

As EFDs become increasingly popular around the world, it is important for policymakers to have empirical evidence of their effectiveness that can guide the further introduction and development of these kinds of devices. The effect of EFDs has already been examined in some countries, but the results – especially those based on macro data – are rather controversial. The experiences of European tax administrations suggest that the introduction of EFDs has not been associated with noticeable increases in VAT revenues, but together with other, simultaneously implemented reforms it can increase tax revenues (Casey – Castro, 2015). In contrast to this, EFDs had a positive effect on VAT revenues in Tasmania, but it was smaller than expected (Fjeldstad et al., 2018). According to Mandari et al. (2017), awareness of the introduction is a key element of taxpayers' acceptance of the EFD system, which can also increase the impact of introduction.

Studies using micro data and methodology similar to our own found more favourable results (Fan et al., 2018). In Sweden, the estimated effect of EFD introduction on reported turnover was 5.2 percent (Awasthi – Engelschalk, 2018). The estimated effect was heterogeneous across sectors, ranging between 0 and 9.5 percent. Moreover, the effect was larger for smaller companies with quarterly VAT returns than for relatively large companies with monthly VAT returns. Using similar data and methods, Awasthi and Engelschalk find that in Rwanda the average effect of EFD introduction was 6.5 percent. In the paper most closely related to ours, Ali et al. (2015) estimated the EFD introduction effect in Ethiopia and found that the short-term effect (at a 1-quarter time horizon) on VAT revenues was 15 percent, while the long-term effect (at a horizon of 6 quarters) was 30 percent. They also found different effects for firms with institutional or personal ownership. The main difference between their paper and ours is that while they estimated the effect over time, we focus on the heterogeneity of the effects across different size categories of firms.

Based on survey data collected by the Hungarian Central Statistical Office (HCSO) to estimate the turnover of the retail sector, the HSCO estimated the effect of OCR introduction at 2.3 percent (HCSO, 2016).[1]

[1] See further use of data of online cash register in Illyés — Varga (2017)

The aim of this paper is to estimate the effect of OCR introduction on reported turnover in VAT returns. We find that the effect is significantly positive. Similarly to Awasthi and Engelschalk (2018), we show that the size of this effect depends strongly on the size and main activity of the enterprises. We find that the effect is smaller for larger companies, which means that estimates that ignore this kind of heterogeneity may be biased.

The paper is organised as follows. In the next section, the environment of OCR introduction is summarised. Next, we present the data set and then describe the methodology. Subsequently, we present the main results from our baseline specification, where the effect of introduction is estimated by a fixed effects panel model. Next, we perform several robustness tests, and the last section presents the conclusions.

LEGAL, TECHNICAL AND ECONOMIC BACKGROUND

In autumn 2012, the Hungarian government decided to introduce online cash registers (OCRs), which are special electronic fiscal devices (EFDs). The final deadline for introduction, which was extended on several occasions, was the end of August 2014. The authorities' original aims in introducing OCRs were the following:

• Increasing the government's tax revenues, by reducing the size of the shadow economy.

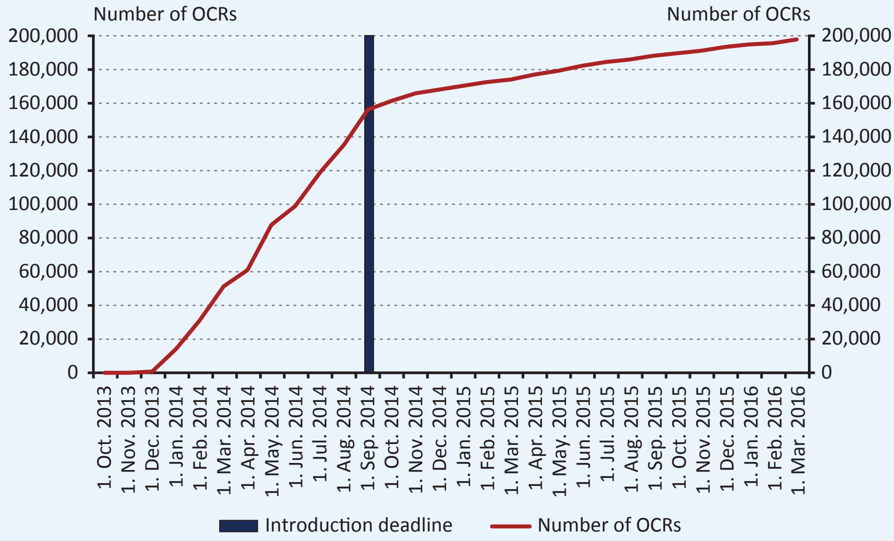
• Reducing the amount of sales without invoices (grey economy).

• Enhancing market competition by reducing tax avoidance.

• Strong support of the control and selection processes of the National Tax and Customs Administration (NTCA).

The first draft of the decree by the Finance Ministry was presented in December 2012, with an original deadline for implementation of 1 April 2013.[2] This deadline was postponed several times, and finally the affected enterprises had to introduce OCRs before 31 August 2014. The number of OCRs increased continuously until the final deadline (see Figure 1). After August 2014, we can also observe stable and moderate growth, but this is due to the openings of new shops that also need to introduce new OCRs.

Figure 1
Number of introduced OCRs over time



Source: National Tax and Customs Administration of Hungary.

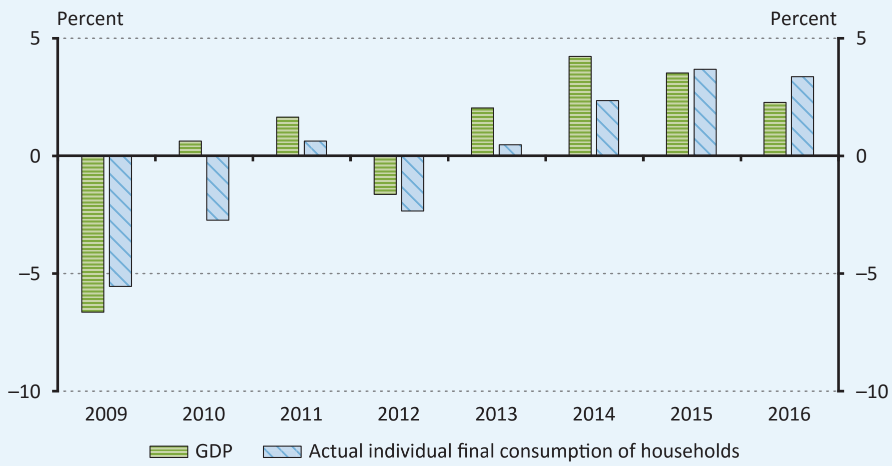
[2] Decree No 3/2013. of 15 February 2013, Ministry for National Economy

By 2016, almost 200,000 OCRs had been introduced by around 100,000 enterprises. In 2015, 75 percent of the total turnover documented by these newly introduced OCRs occurred in the retail sector, and another 8 percent was generated in the accommodation and food services (AFS) sector. In this paper we focus on these two sectors, and thus our turnover-based data coverage is 83 percent. Some enterprises from the rental and repairs sectors also had to introduce OCRs, but due to the small number of these firms, they are not analysed in this paper.

The most important part of the OCR is a kind of fiscal memory that collects all of the relevant tax information (opening and closing time of the register, blackouts, value and tax rate of the sold items, etc.) and saves it indefinitely. No information is allowed to be deleted. The memory is part of the register and must be placed inside the casing of the cash register. No hidden software can run on the register, and three independent experts must certify this. The device not only saves the information, it also transfers it to the National Tax and Customs Administration, typically every 30 minutes. A special mobile internet connection is used to send the information. The information is encrypted before it is sent, and a special encoding technique prevents ex-post modification of the data. The National Tax and Customs Administration collects the information in a server, and can therefore monitor the sales of the registers and the current content of the register.

In order to properly assess the effect of OCR introduction, we need to understand the macroeconomic background during the introduction period, especially because the spread of OCRs occurred in the middle of a recovery period in the Hungarian economy. As the Great Recession was preceded by procyclical and expansionary fiscal policy, the consequences of the global economic crisis proved to be more severe in Hungary than in most other countries in the region. In 2009 Hungary's gross domestic product dropped by 6.6 percent, household consumption contracted by 5.5 percent, and the second wave of the crisis caused a GDP decrease also in 2012. In the following years both GDP and household consumption grew by around 3 percent, and therefore this can be regarded as a relatively long recovery period. The gross domestic product reached its pre-crisis level in 2014, while household consumption exceeded it only in 2017, almost a decade after the collapse of Lehman Brothers (Figure 2).

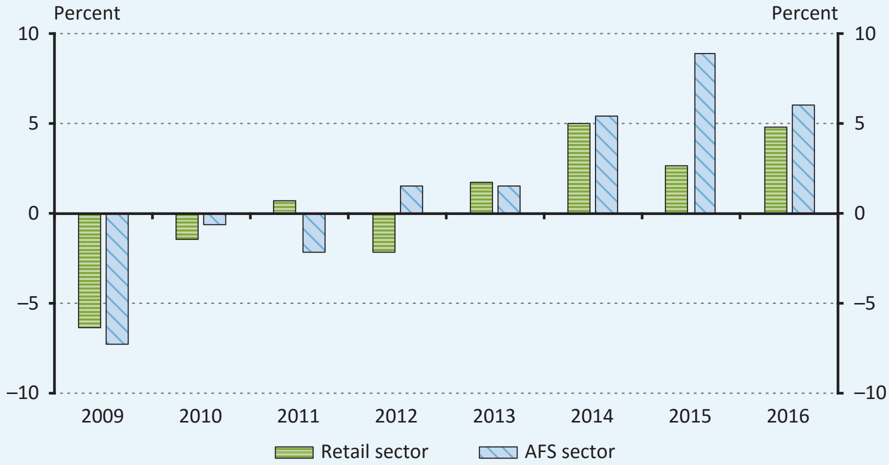
Figure 2
Growth rate of real GDP and household consumption in Hungary (yoy)



Source: AMECO.

Figure 3 shows the recent developments in the two sectors we analyse. In 2009, when the global economic crisis had the most severe effect, retail trade turnover dropped by 6.4 percent, and over the next four years (2010-2013) its growth rate fluctuated around zero. In 2014, when most OCRs were installed, the index jumped to 5 percent, followed by a year of moderate growth (Figure 3). In the AFS sector we can observe a similar pattern. Real turnover fell by more than 7 percent in 2009, and the growth rate turned positive from 2012. In 2014 the growth rate advanced to 5.5 percent and then to 9 percent in 2015.

Figure 3
Growth rate of real turnover in retail trade and in AFS activities (yoy)



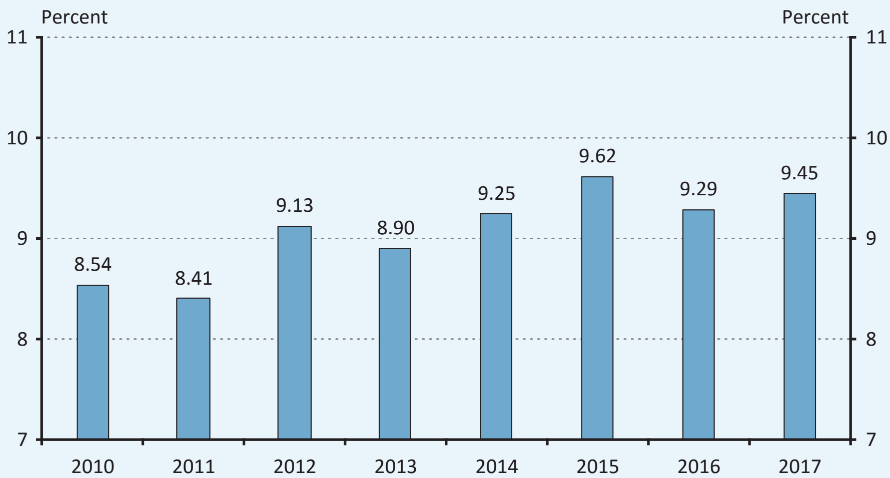
Source: HCSO.

Actual introduction of OCRs took place from the end of 2013 until the start of 2015, but most firms installed the new tool(s) in 2014. This gradual installation means that its impact on the year-on-year figures may be split between 2014 and 2015, and so it is worthwhile to take a closer look at these two years. In the retail trade sector, the two-year growth rate from 2013 was 7.9 percent in real terms and 8.6 percent in nominal terms. In the AFS sector, from 2013 to 2015 turnover increased by 14.9 percent in real terms and 21.9 percent by nominal terms.

One of the main goals of introducing OCRs was to reduce the shadow economy, and thus it is worthwhile to analyse total VAT revenue as well. This is particularly important from the fiscal point of view, since VAT makes the largest contribution to the revenue side among taxes, accounting for almost one quarter of total tax revenues. Although analysing VAT by comparing it to the gross domestic product is a commonly used method as it handles the issue of inflation and changes in the tax base, it is worth emphasising that GDP differs from the VAT tax base in several ways (for instance, the latter does not include exports and consumption in kind). Nonetheless, GDP is a widely used and easily accessible figure, so we follow the literature and use this indicator.

At the start of the decade, total VAT revenue amounted to around 8.5 percent of the gross domestic product. The general statutory tax rate was increased from 25 percent to 27 percent in 2012 and this explains the rise in the VAT-to-GDP ratio to 9.1 percent. After the introduction of OCRs the indicator rose further, to reach 9.6 percent in 2015 (Figure 4).

Figure 4
Total VAT revenue (percent of GDP)



Source: HCSO.

This means that between 2013 and 2015 the VAT-to-GDP ratio rose by approximately the same amount as in 2012 after the VAT increase. The question is to what extent can this remarkable shift be explained by introducing OCRs. Since there was no other significant change in the legal environment between 2013 and 2015, the rise in the VAT-to-GDP ratio may indicate the reduction of the shadow economy. This is true under the assumption that the extent and annual change of the hidden economy is measured properly in the course of the GDP calculations. A more detailed comparison of VAT revenue to GDP is made by Poniatowski et al. (2019), who calculated the VAT Gap by defining the difference between the total theoretical VAT liability and the amount of actually collected VAT. This VAT gap decreased from 21 percent to 16 percent between 2013 and 2015 in Hungary.

Summarising the above findings, during the period of introducing OCRs there was a clear increase in the turnover of both analysed sectors, especially in AFS. Nevertheless, this period coincides with a recovery in the economy as a whole, making it difficult to distinguish the effect of the new instrument from the effect of the favourable macroeconomic environment. Remarkable growth was recorded in the VAT-to-GDP ratio, possibly indicating that the introduction of OCRs had some effect on the reduction of the shadow economy. Since the analysis of aggregate numbers is not decisive in judging the effect of OCRs, microdata analysis is required.

DATA AND FILTERING

This section describes the linked microdata that we use to estimate the panel econometric model. The main data sources were individual VAT returns, linked with the individual OCR database and the database of individual corporate income tax returns. These different sources contained different kinds of data from different number of enterprises at different observation frequencies (Table 1).

Table 1
Summary of the applied databases

Type of database	Period	Number of observations	Frequency
VAT	2012 – 2016	2,820,762 VAT returns*	annual, monthly, quarterly
OCR – individual turnover data	2015	101,916	monthly
OCR – date of the first cash register installation	2013 – 2015	101,911	monthly
Corporate income tax	2012 – 2016	414,3622	annual

** Consisting of annual, quarterly and monthly VAT returns.*
Source: National Tax and Customs Administration.

In the empirical analysis we focused on reported turnover. Reported turnover can be calculated in several ways from the VAT returns, and different institutions use different definitions. We used a definition which is simple and includes all turnover that should go through the OCRs. We added up 4 lines in the return: sales with 27% VAT, sales with 18% VAT, sales with 5% VAT and sales with other taxes. Using alternative definitions (e.g. adding sales free of VAT due to public interest or contribution sales, etc.) has no effect on the main results.

One of the main issues of the econometric specification was the question of observation frequency, as some companies prepare monthly VAT returns, while others file quarterly or annual VAT returns. We also have some mixed cases, when enterprises change the frequency of filing tax returns, which occurs when the annual turnover exceeds a certain threshold level. In order to create a dataset in which the observation frequency is homogeneous, we aggregated the monthly data to the quarterly level and excluded the companies with annual VAT returns. This solution is reasonable as the turnover of companies with annual VAT returns represents approximately 1 percent of total turnover in the retail sector and 2.6 percent of total turnover in the ACF sector, and if we merge the two sectors into one it represents 1.1 percent of total turnover. We have information about the number of installed cash registers at the end of every month. When we aggregated to quarters, we used the information from the end of the second (middle) month of the quarter. This was the most reasonable choice and also had an additional advantage as the final installation deadline was August 2014, which was the second month of the third quarter in 2014.

Since some companies installed more than one OCR, we also had to provide an exact definition for the most important variable in our econometric specification, the installation date. In our baseline specification, we decided to use the installation date of the first OCR. The robustness section of this paper (see page 17) shows the results with two alternative definitions: the quarter with the largest number of new OCRs and the quarter with the last OCR installation during the introduction period. The main results of the paper are robust to these modifications.

Prior to estimation, we applied two different data filtering methods. First, we omitted those observations that were not informative for our research question and then we carried out the usual data cleaning steps (e.g. outlier filtering). We initially had a total of 153,636 enterprises in the retail and AFS sector, but the final panel dataset that we use for the estimation includes only 16,050 firms.[3]

The starting database contained all enterprises operating in the retail trade and AFS sector between 2012 and 2016 (NACE 47, 55-56 divisions). In the first step we dropped the companies which did not have to install OCRs, and then we also omitted those enterprises which did have an online cash register, but a large proportion of their turnover was not registered by any OCR. The latter occurs if the main operation of the company is not in the retail or AFS sector, but only a minor part of the turnover comes from these two sectors. To find these enterprises we used the ratio of VAT turnover and OCR turnover in 2015. In this ratio, the numerator includes all kind of activities that are reported in the VAT returns, while the denominator only contains turnovers that are registered by one of the online cash registers. The ratio of the two indicates the relative importance of those activities that are not covered by the online cash registers. Specifically, we decided to keep the firms where this VAT/OCR indicator was less than 1.5. In this first step, our sample size decreased from 153,636 to 48,176 firms (see Table 2).

Table 2
Number of observations after data filtering (detailed table in Appendix A)

	N – cumulated	
	Retail sector	**AFS**
Related section	106,074	47,562
Step 1 – target group	32,813	15,363
Step 2 – data cleaning	11,136	4,914
Final sample	11,136	4,914

Source: National Tax and Customs Administration

In our baseline specification we decided to keep the enterprises whose VAT/OCR indicator is less than 1.5. This means that if the VAT turnover is more than 50 percent higher than the OCR turnover, then activities not related to OCRs are significant and we wanted to avoid possible estimation bias due to these activities. The robustness section (from page 19) contains results with these alternative assumptions.

In the second step we dropped outliers and observations with unrealistic data, and companies with very few observations. We also dropped observations where the installation date was after the deadline (31 August 2014), since we assume that those correspond to new companies and are not informative about the effect of OCR installation. As one of our explanatory variables is in the corporate income tax (CIT) return dataset, we also dropped those companies which did not have a corporate income tax return or reported missing data for this variable. This occurred typically in the case of small enterprises.

[3] The filtering step was preceded by the data cleaning, to drop the ambivalent data. The number of outliers was negligible, but their effect could have caused serious bias in the results, so a microsimulation was made to check the correct filling of VAT returns.

MODEL SPECIFICATION

Our main goal is to identify the effect of introducing OCRs on turnover, and distinguish it from other factors that might have influenced it. We do this by exploiting the heterogeneity in installation dates, and estimate the following panel econometric model with company and time fixed effects:

$$y_{i,t} = \beta_0 + \beta_1 o_{i,t} + \beta_2 w_{i,t} + \gamma_t + \delta_i + \varepsilon_{i,t}$$

where

$y_{i,t}$ is the log reported turnover of the ith company at quarter t;

$o_{i,t}$ is the OCR dummy, 1 if the company i has at least one operating OCR in quarter t and 0 otherwise;

$w_{i,t}$ is the log reported total wage cost for company i in quarter t. This variable is taken from the yearly CIT return, so its value is fixed in all four quarters of the year;

γ_t time fixed effect at quarter t;

δ_i company fixed effect for the ith company;

$\varepsilon_{i,t}$ residual of the ith company at quarter t.

Our parameter of interest is β_1, which shows the relative change in reported turnover (measured in log points) after the introduction of the first OCR. With this specification we avoid comparing cross-sectional to companies which have not introduced OCRs and thus are possibly different from those which had.

The key condition for parameter β_1 to measure the causal effect of OCR introduction is the exogeneity of introduction time. As mentioned before, the introduction deadline was postponed several times, due to technical difficulties with installing the OCRs: as thousands of enterprises ordered OCRs at the same time, the distributors were only able to deliver the devices gradually. This means that actual installations took place several months, and sometimes even half a year after submission of the order, and this delivery delay could not be influenced by the enterprises. This assumption on the randomness of installation dates is further supported by the descriptive statistics of Table 3.

Table 3
Descriptive statistics of the introduction dates in the sample

Date of OCR installation	2013Q4	2014Q1	2014Q2	2014Q3
Number of companies	211	6,056	4,500	5,283
Share of retail companies	67%	70%	70%	68%
Share of companies with 1 OCR	60%	54%	53%	60%
Median size*	23,390	20,496	18,916	19,038

Source: Own calculations
** average yearly turnover before introduction in thousand HUF.*

The sectoral distribution of the companies that installed their first OCRs is very similar across quarters. The share of companies with one OCR is somewhat bigger for the first and the last quarter, but not decisively. The median size of the companies, measured by average yearly turnover prior to the first installation, is almost the same for the last three introduction quarters (2014Q1-Q3). Only the few companies introducing OCRs in 2013Q4 have, on average, 20% larger turnover, but this is unlikely to distort the results. As the size distribution of firms is extremely skewed, we report the median sizes for the different installation dates.

Different seasonality in different sub-groups could distort our estimations, especially if seasonality was correlated with the OCRs' introduction dates. Therefore, we estimated the effect of introduction both in seasonally adjusted and non-adjusted turnover data, and obtained almost the same results. We decided to use the non-seasonally adjusted data in our baseline specification.

We estimated the above regression on the effects of OCR introduction separately for the two sectors and also for different firm sizes. This way we allowed for sector- or size-specific time fixed effects, which would not have been possible if we simply used interaction variables between the OCR introduction date and sectors or firm sizes. These estimated times fixed effects are indeed different in different sectors and for different firm sizes (e.g. the general growth rate of smaller companies' turnover was lower). Firm size is measured by yearly average turnover (from VAT returns) prior to OCR introduction.

When deciding about the number of size categories for firms, we face the following tradeoff: with more size categories we can better observe the size-specific heterogeneity, but the estimated coefficients have larger standard errors as the number of observations decreases. We tested whether the estimated OCR effects in different size categories were significantly different from each other and used this information to construct our baseline size categories. Specifically, we ran regressions for 20 different size categories, within each possible sector (accommodation, food services, and different industries within the retail sector). In our final specification companies are categorised into two main sectors:

1. retail sector as a whole,

2. accommodation and food services (AFS) sector.

We excluded the fuel retail sector, where we only had 204 companies and which was small with insignificant OCR effects (probably due to the fact that excise tax rules make it difficult to cheat VAT on fuel).

Table 4
Composition of the final sample

Name of subsample	Number of analysed firms	Lower bound, thousand HUF*	Upper bound, thousand HUF*	Analysed turnover, thousand HUF*
Small retail	2,228	0	7,400	9,112,088
Medium retail	2,227	7,400	15,100	24,191,779
Large retail	6,681	15,100	-	2,776,842,273
Small AFS	983	0	6,920	4,066,690
Medium AFS	983	6,920	12,900	9,442,928
Large AFS	2,948	12,900	-	196,195,506

Source: Own calculations
** average yearly turnover before introduction*

In terms of size categories, we divided both sectors into three categories: small, medium and large firms. This means that we estimated the model for 6 different subsamples (see the rows of Table 4). Small companies were in the lowest size quintile, medium companies in the second quintile, and large companies were in the third, fourth and fifth quintiles (meaning that more than half of the companies were categorised as large). The decision to merge three quintiles into one single size category was based on estimated size-specific OCR coefficients, which were not significantly different from each other within the three largest quintiles. As the division into size quintiles was conducted separately in the two sectors, the size limits (that separate the different size categories) were somewhat different in the two sectors. this decision was motivated by having sector-specific quintiles with the same number of companies and thus similar standard errors. The bounds were very close in the retail and AFS sectors (columns 3-4 of Table 4), so the different size boundaries probably do not cause distortions.

RESULTS

Our results show an increase in turnover after OCR introduction in all sectors and all size categories. However, the sector- and size-specific OCR effects are significantly different from each other. In general, OCR effects are larger for smaller companies and in the AFS sector. In the retail sector the estimated OCR effect is not significant for large companies, but the effect is 5.4 percent and 23.0 percent for medium and small companies, respectively. In the AFS sector, the effects for small, medium and large companies were 35.1 percent, 13.2 percent and 6.7 percent, respectively (Table 5 and Figure 5).

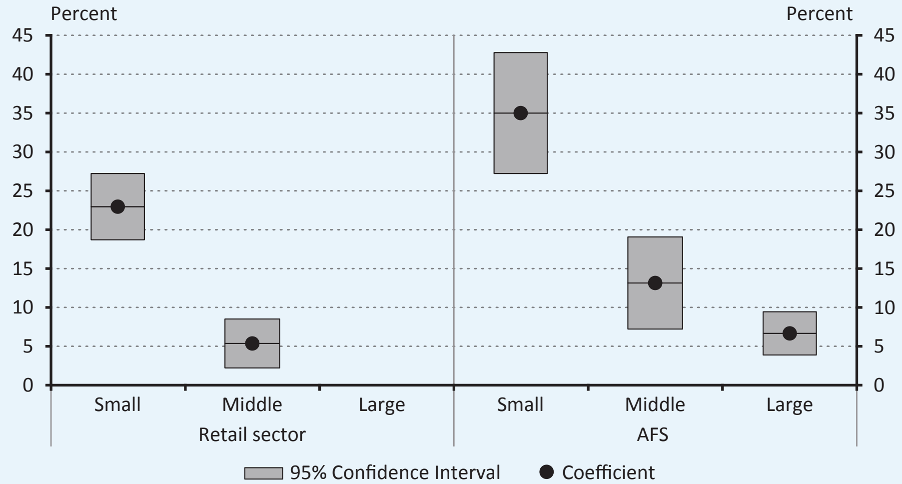
Table 5
Summary of main results: estimated beta_1 coefficient and their standard errors

Subsample	Coefficient	Standard error
Small retail	23.0%	2.2%
Medium retail	5.4%	1.6%
Large retail	0.9%	0.7%
Small AFS	35.1%	4.0%
Medium AFS	13.2%	3.0%
Large AFS	6.7%	1.5%

Source: Own calculations

These findings on significantly positive turnover effects are similar to the results of other papers in the literature that use micro data to analyse the effect of EFD introduction in other countries. Some of these papers have also shown that the effect depends strongly on the size of the company, which coincides with our intuition. However, these previous calculations were not as detailed as ours.

Figure 5
Summary of main results: estimated beta_1 coefficients and their 95% confidence intervals



Source: Own calculation.

The estimated coefficients show the average OCR effects within the subsamples. For policy evaluation purposes it is useful to have an estimation of the total OCR effect. This also enables us to compare the additional tax revenues from higher sales to the introduction and operation costs of the system. However, our model has serious limitations in this respect, because of the extremely concentrated turnovers. The total effect of OCR introduction on reported turnover depends almost entirely on our estimation for large retail companies, as they account for 92 percent of the total turnover in our sample. For this group our estimate is 0.9 percent and is not significantly different from 0. It makes an enormous difference for the total turnover effect if we calculate it with an estimated parameter of 0, 0.9 percent or 2.3 percent (the upper bound of the 95 percent confidence interval). This limitation is due to the extreme concentration of turnover across the different size categories.

Another important issue is concentration within size categories. As discussed earlier, in our model large retail companies are in the upper 3 size quintiles of the sample. There are 6,681 such firms. Turnover is extremely concentrated among these companies as well. Within the large retail firms, the largest company accounts for 21 percent of sales, and the top 10 and top 100 have shares of turnover amounting to 56 percent and 78 percent, respectively. Our estimates are average estimates for the size categories. It is likely that the true effects are different for specific firms, probably +5 percent for some of them, while 0 for others. For the total effect it makes a huge difference if among the top 100 companies we had 10, 5, 2 or 0 companies with a +5 percent effect and our methodology is not suitable to estimate this. The concentration causes the biggest uncertainties for the large retail firms, but nevertheless it is also present in other subsamples, to a lesser extent. For large companies of the ACF sector the top company accounts for 3.7 percent of the total sales, while the top 10 and top 100 are responsible for 13 and 34 percent, respectively, of the total turnover of 2,948 companies.

Keeping in mind these limitations, we present our best estimates for the magnitude of the total OCR effect. In order to assess the overall aggregate effect of OCR introduction on growth in turnover, we extrapolated the results we received for the estimation sample to all enterprises in the two sectors. The size categories were the same as above, for all the companies which had installed at least one OCR, and where the VAT/OCR turnover was less than 1.5. We found that the introduction of OCRs contributed to annual growth in the whole retail sector by 0.4 percentage points.

This number is relatively small because of several factors. First, one third of the companies in the retail sector did not have to install OCR, either because these companies sell products the price of which is more than HUF 100,000, or because these companies were operating in a sub-sector that was not obliged to install the new devices. But the most important explanation is the same as above: distribution of the turnover is strongly concentrated not just in the sample, but in the whole population as well. As can be seen above, for the retail sector we found that OCR introduction had a sizeable effect on turnover for small and medium-sized companies. However, among the large companies we could not identify such an effect and this group of enterprises is responsible for 95 percent of the total turnover in the sector (see Table 6).

Table 6
Descriptive statistics for the subgroups of analysed sectors

Size of companies	Number of firms		Individual turnover (thousand HUF)		Total turnover (billion HUF)	
	Number	Share	Min	Max	Total	Share
Retail sector						
Small	11230	38 %	0	7400	93	3 %
Middle	5831	20 %	7400	15100	76	2 %
Large	12726	42 %	15100	-	3471	95 %
Total	29787	100 %				100 %
Catering and accommodation sector						
Small	5914	44 %	0	6920	42	11 %
Middle	2772	20 %	6920	12900	32	9 %
Large	4850	36 %	12900	-	301	80 %
Total	13536	100 %				100 %

Source: Own calculations

In the AFS sector, we find that the introduction of OCRs contributed to the annual growth of the sector by 4.3 percentage points. This number is also somewhat smaller than the effect in the three size categories, mainly because one third of the companies did not have to install OCRs (similarly to the retail sector).

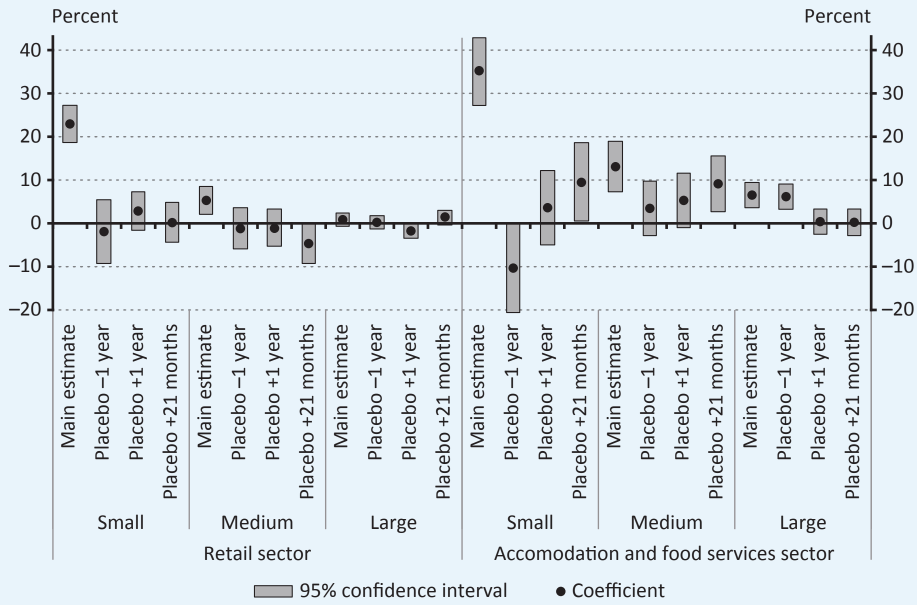
The specification guarantees that the measured OCR effect is only due to the introduction of OCRs. It is the total long-term effect of OCR introduction (as opposed to the short-term effect in the quarter of the introduction). This estimate, however, should be considered as a lower bound for the true effect. The reason is that we did not consider effects that were unrelated to the connection of the first devices. For example, it may be the case that when the legislation was passed in parliament or when the media wrote about it, some firms started to change their behaviour. This “announcement effect” cannot be estimated in our specification as there is no firm-specific heterogeneity in this respect; thus its impact is captured by the time fixed effects. We also did not measure possible further effects on other types of taxes.

ROBUSTNESS TESTS

As a first test, we re-estimate our baseline model with placebo OCR introduction dates. We expect that the estimated OCR effects at these false introduction dates are not significantly different from zero, and therefore there is no systematic distortion in our dataset that would lead us to falsely detect an OCR effect when in reality there is no such effect. We used 3 different placebo introduction dates: 1 year before the real introduction date, 1 year after the introduction date, and 21 months after the introduction. We used the latter placebo date to check once more whether seasonality of turnovers could in any way lead to estimation bias.

The results of Figure 6 show that the OCR effects that we found in our baseline model do not exist in the models with placebo introduction dates. Estimated coefficients are almost always closer to 0 than our true estimates, and they are mostly insignificant.

Figure 6
Estimation results with placebo introduction dates

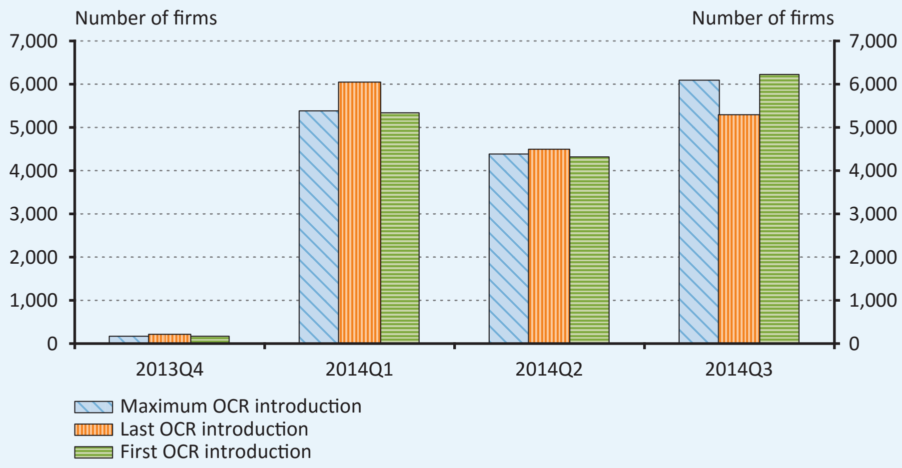


Source: Own calculation.

In our second robustness test, we re-estimated our baseline model with alternative definitions of OCR installation dates. In the baseline specification the OCR dummy variable changes to 1 when the company introduces the first OCR (and remains 1 thereafter).

We tested two alternative definitions for the OCR introduction dates: the quarter of the last OCR installation, and the quarter with highest number of new installations. This latter definition is reasonable as larger companies often installed only a few OCRs in the beginning as a test, and then installed most of the new machines at a later date (and may have continued installations at a slower rate).

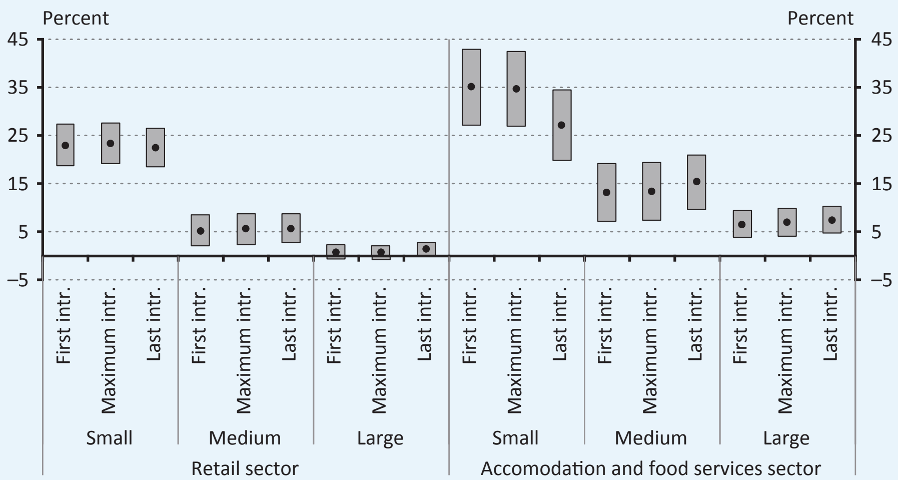
Figure 7
OCR introductions by quarter



Source: National Tax and Customs Administration of Hungary.

Figure 7 shows the number of installations by quarter, according to all 3 alternative definitions of the introduction date. In some cases, the quarter of the first, last and maximum number of installations can be different from each other. But as most companies have only 1 or 2 OCRs, the differences in the distribution of introduction dates are not that large. In fact, for 92 percent of the companies in our sample the OCR installations occurred in one quarter and thus all three definitions are the same. Therefore, it is perhaps not surprising that the estimated coefficients are very similar to our baseline estimates and are never significantly different from these (see Figure 8).

Figure 8
Estimates with different definitions of the introduction date variable



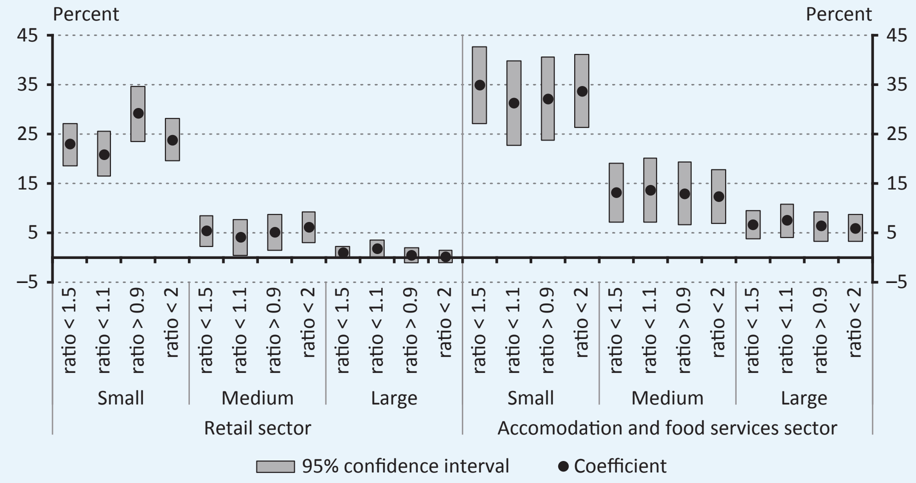
Source: Own calculations.

During the data selection process, we excluded companies which had relatively high revenues that did not have to go through OCRs. The reported turnover in VAT returns, which is the variable from which we actually identify the OCR effect, is not divided into OCR and non-OCR turnover. As we expect that OCRs affect only the turnover that is registered by them, in our baseline specification we excluded those firms where the VAT/OCR ratio was smaller than 1.5.

In a third robustness test, we re-estimated our model with alternative VAT/OCR cutoff numbers in the data selection process: 1.1 and 2. In yet another run, we kept the 1.5 as the upper limit for the VAT/OCR ration, but introduced 0.9 as a lower threshold. Ratios much lower than are theoretically impossible, and they usually reflect data errors which were frequent especially in the first years of OCR operations. While re-estimating the model for different VAT/OCR sales ratios, we kept the baseline size categories constant. This way the same companies belonged to the same size categories across the different specifications, but the number of observations (in each size categories) vary, rendering the standard errors not entirely comparable.

The estimated coefficients for the alternative VAT/OCR cutoffs are always very similar to our baseline estimates and the differences are never significant (see Figure 9).

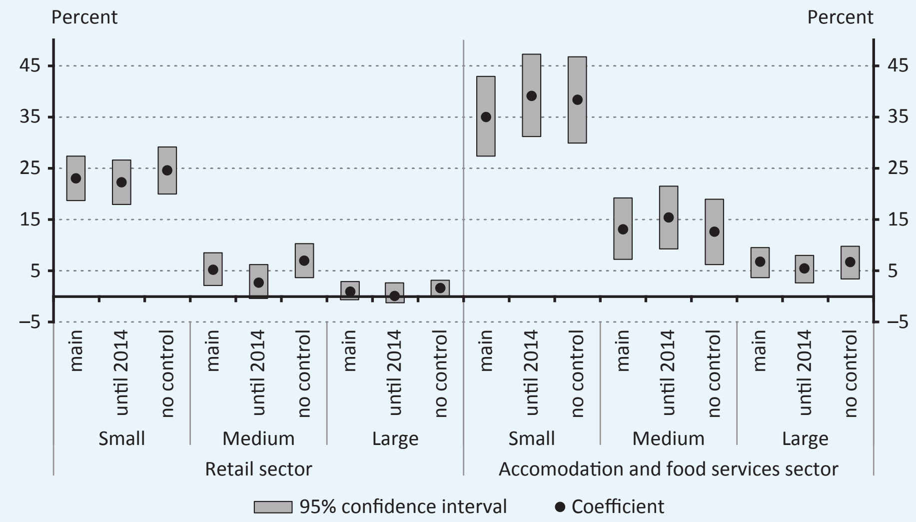
Figure 9
Estimations for alternative VAT/OCR cutoffs



Source: Own calculations.

Finally, we re-estimated the model with two further modifications. In the first modification (labelled by "until 2014" in Figure 10) we dropped data from 2015 and 2016, and in the second (labelled by "no control") we dropped the wage cost from the control variables. As every OCR introduction had to be carried out by 2014Q3, the variation that we exploit to identify the OCR effect is unaffected by the last two years of data (2015 and 2016). As a consequence, estimates are not significantly different from our baseline estimates (though coefficients for medium and large retail companies become somewhat smaller). This result ensures that the measured effect was really caused by OCR introduction and is not influenced by later developments in turnover.

Figure 10
Estimates with another two alternative specifications



Source: Own calculations.

The alternative specification “no control” re-estimates the model without the control variable “personal benefits”. The resulting estimates do not differ significantly from those in our baseline specification. We ran this test as one might suspect reverse causality (i.e. that the OCRs introduction could have an effect on it in a very indirect way), this result ensures that these concerns about possible endogeneity are not justified.

CONCLUSIONS

With the spread of the internet and digitalisation, an increasing number of countries have introduced online cash registers to reduce their shadow economy. The Hungarian government made it compulsory to install online cash registers in some sectors in 2014. The switch from the old cash registers to the new ones took place gradually and mostly affected the retail sector and the accommodation and food services (AFS) sector. During this process almost 200,00 OCRs were installed by approximately 100,000 companies. In this paper we use panel econometric techniques to identify the effect of this measure on the reported turnover of the enterprises. We assume that the introduction of the OCRs itself does not change the operation of the companies, so the resulting extra turnover – after controlling for other factors – can be considered as the reduction of the shadow economy.

To quantify this effect, we use a linked firm-level dataset of Hungarian enterprises on their VAT returns, corporate income tax returns and online cash registers data. We find that the introduction of online cash registers has a remarkable effect on the reported turnover of the enterprises in the affected sectors. This effect, however, is heterogeneous across different size categories. For small companies the effect was a 23.0 percent turnover increase in the retail sector, and a 35.1 percent increase in the AFS sector. For the middle-sized companies, we also find significant increases: 5.4 percent and 13.2 percent in the retail and AFS sector, respectively. For large companies, we find a significant effect (6.7 percent) only in the AFS sector. The overall contribution of OCR introduction to the annual turnover growth of the retail sector is 0.4 percentage points, which is relatively small because around 95 percent of the total sectoral turnover is concentrated at large companies, for which we could not identify any effect. In the ACF sector, the introduction of the online cash registers contributed to the annual growth rate of the sector’s turnover by 4.3 percentage points.

References

Ali, Merima – Shifa, Abdulaziz – Shimeles, Abebe – Woldeyes, Firew (2015): Information technology and fiscal capacity in a developing country: Evidence from Ethiopia. ICTD Working Paper 31. Institute of Development Studies.

Awasthi, Rajul – Engelschalk, Michael (2018): Taxation and the Shadow Economy. Policy Research Working Paper No. 8391, World Bank, Washington, DC

Casey, Peter – Castro, Patricio (2015): Electronic Fiscal Devices (EFDs) An Empirical Study of their Impact on Taxpayer Compliance and Administrative Efficiency. No. 15-73. International Monetary Fund.

Eilu, Emmanuel (2018): Adoption of electronic fiscal devices (EFDs) for value-added tax (VAT) collection in Kenya and Tanzania: a systematic review. African Journal of Information and Communication 22, 111-134.

Fan, Haichao – Liu, Yu – Qian, Nancy – Wen, Jaya (2018): The Dynamic Effects of Computerized VAT Invoices on Chinese Manufacturing Firms. NBER Working Paper No. 24414

Fjeldstad, Odd-Helge – Kagoma, Cecilia – Mdee, Ephraim – Sjursen, Hoem Ingrid – Somville, Vincent (2018): The Customer is King: Evidence on VAT Compliance in Tanzania. ICDT Working Paper 83.

HCSO (2016): A hálózatba kötött pénztárgépek gazdaságfehérítő hatásának vizsgálata. Avaibla onile: http://www.ksh.hu/docs/hun/xftp/idoszaki/pdf/opg.pdf

Ilyés, Tamás – Varga, Lóránt (2017): Acceptance of Payment Cards by Retailers in Hungary Based on Data of Online Cash Registers. Financial and Economic Review, 17(1), 83-109.

Mandari, Herman – Koloseni, Daniel – Nguridada, Jerome (2017): Electronic fiscal device (EFD) acceptance for tax compliance among trading business community in Tanzania: the role of awareness and trust. International Journal of Economics, Commerce and Management, 5(3), 142-158.

Mayer-Schönberger, Victor – Cukier, Kenneth: (2013). Big data: A revolution that will transform how we live, work, and think. Houghton Mifflin Harcourt.

OECD (2013): Electronic Sales Suppression: A threat to tax revenues. Available online: https://www.oecd.org/ctp/crime/ElectronicSalesSupression.pdf

Poniatowski, Grzegorz – Bonch-Osmolovskiy, Mikhail – Duran-Cabré, José María – Esteller-Moré, Alejandro – Śmietanka, Adam (2019): Study and Reports on the VAT Gap in the EU-28 Member States: 2019 Final Report. Case Research Paper 483.

Varian, Hal R. (2010): Computer mediated transactions. American Economic Review 100(2), 1-10.

Appendix A

DATA FILTERING

Table 1
Number of observations after data filtering – Retail sector

Type of data filtering	Filter	N – change	N – cumulated
Step 1 – target group	1.1 Retail trade between 2012 and 2016		106,074
	1.2 there are OCR	– 57,762	48,312
	1.3 there are manly retail trade activity (if the VAT/OCR turnover < 1.5)	– 15,499	32,813
Step 2 – data cleaning	2.1 outliers	– 218	32,595
	2.2 missing data*		11,136
	Final sample		11,136

Step 2.2 missing data (details):

There is at least one quarterly data	– 2,540	30,055
Date of the first cash register installation was completed by August 2014	– 3,441	26,614
Other filters:	– 5,140	21,474
1. where the date of the first cash register installation and the first VAT turnover are in the same period		
2. where the date of the first cash register installation are before the date of the first VAT turnover		
3. where there are more than 2 changes between quarterly and annual frequency		
There are Corporate Tax returns	– 9,190	12,284
The personal benefit variable has a value		11,136

Table 2
Number of observations after data filtering – AFS sector

Type of data filtering	Filter	N – change	N – cumulated
Step 1 – target group	1.1 Accommodation and food service activities between 2012 and 2016		47,562
	1.2 there are OCR	– 25,455	22,107
	1.3 there are manly retail trade activity (if the VAT/OCR turnover < 1.5)	– 6,744	15,363
Step 2 – data cleaning	2.1 outliers	– 250	15,113
	2.2 missing data*		4,914
	Final sample		4,914

Step 2.2 missing data (details):

There is at least one quarterly data	– 1,092	14,021
date of the first cash register installation was completed by August 2014	– 2,332	11,689
Other filters:	– 2,798	8,891
1. where the date of the first cash register installation and the first VAT turnover are in the same period		
2. where the date of the first cash register installation are before the date of the first VAT turnover		
3. where there are more than 2 changes between quarterly and annual frequency		
There are Corporate Tax returns	– 3,407	5,484
The personal benefit variable has a value	– 570	4,914

Appendix B

REGRESSION OUTPUTS

Table 3
Main Results (Dependent variable: Log Revenues)

	Small Retail	Medium Retail	Large Retail	Small AFS	Medium AFS	Large AFS
	-1	-2	-3	-4	-5	-6
OCR Introduction	0.230***	0.054***	0.009	0.351***	0.132***	0.067***
	(0.022)	(0.016)	(0.007)	(0.040)	(0.030)	(0.015)
Log Wage	0.426***	0.450***	0.575***	0.500***	0.443***	0.513***
	(0.008)	(0.007)	(0.004)	(0.012)	(0.012)	(0.006)
Observations	30,906	36,742	122,01	12,438	15,562	52,324
R^2	0.104	0.120	0.187	0.133	0.092	0.131
F Statistic	1,666.476*** (df = 2; 28657)	2,361.926*** (df = 2; 34494)	13,220.320*** (df = 2; 115308)	874.509*** (df = 2; 11434)	738.851*** (df = 2; 14558)	3,713.884*** (df = 2; 49355)

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 4
Results by Quintile (Dependent variable: Log Revenues)

	Retail 1st Quintile	Retail 2nd Quintile	Retail 3rd Quintile	Retail 4th Quintile	Retail 5th Quintile	AFS 1st Quintile	AFS 2nd Quintile	AFS 3rd Quintile	AFS 4th Quintile	AFS 5th Quintile
	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10
OCR Introduction	0.230***	0.054***	0.010	0.007	0.009	0.351***	0.132***	0.080***	0.034	0.081***
	(0.022)	(0.016)	(0.014)	(0.013)	(0.012)	(0.040)	(0.030)	(0.028)	(0.026)	(0.022)
Log Wage	0.426***	0.450***	0.532***	0.586***	0.610***	0.500***	0.443***	0.557***	0.482***	0.503***
	(0.008)	(0.007)	(0.006)	(0.006)	(0.006)	(0.012)	(0.012)	(0.011)	(0.010)	(0.009)
Observations	30,906	36,742	39,024	40,892	42,094	12,438	15,562	16,647	17,523	18,154
R^2	0.104	0.120	0.155	0.191	0.223	0.133	0.092	0.134	0.116	0.147
F Statistic	1,666.476*** (df = 2; 28657)	2,361.926*** (df = 2; 34494)	3,377.695*** (df = 2; 36776)	4,560.555*** (df = 2; 38644)	5,714.568*** (df = 2; 39846)	874.509*** (df = 2; 11434)	738.851*** (df = 2; 14558)	1,213.195*** (df = 2; 15644)	1,088.926*** (df = 2; 16519)	1,475.945*** (df = 2; 17150)

*Note: *p<0.1; **p<0.05; ***p<0.01*

MNB OCCASIONAL PAPER 137

2019. december

Print: Prospektus Kft.

8200 Veszprém, Tartu u. 6.

mnb.hu

1054 BUDAPEST, SZABADSÁG TÉR 9.