Fines versus Imprisonment for the Issuance of Bad Checks: Evidence from a Natural Experiment in Turkey†

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Abstract: We investigate whether the February 2012 amendments to the Check Law in Turkey that replaced imprisonment with monetary and administrative fines for writing bad checks were a driver of the surge in the frequency of bad checks since late 2011. As the planned amendments were announced well in advance, check issuance behavior was potentially altered before the amendments officially took effect. To capture this, we use the cumulative volume of related keyword searches on the internet as a proxy for the legal change. We find that unlike the case during the global financial crisis, the surge in bad checks around 2012 cannot be explained by the changes in the economic environment unless the February 2012 legal change is also controlled for. We also show that the surge in the incidence of bad checks was not accompanied by an increase in their average value. Finally, we provide evidence that economic agents adapt fairly rapidly to the legal change by adjusting their screening and monitoring capacities, which helps to reverse the surge in bad checks within a year. Overall, our findings suggest that sanctions need not be harsh to deter wrongful behavior as long as appropriate infrastructures that will enable efficient behavioral adjustments are in place.

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Keywords: Checks, Bad Checks, Decriminalization, Deterrence, Natural Experiment, Turkey

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1. Introduction

The economic approach to criminal law posits that criminals are not necessarily different from other people, they simply face different expected costs and benefits of committing a crime and engage in the criminal activity if the expected benefits outweigh the expected costs (Becker, 1968). The primary role of criminal sanctions is thus not to punish wrongdoers for past behavior but to provide appropriate incentives for rational, forward-looking individuals to behave in a socially desirable manner in the future. Designing appropriate sanctions is a crucial objective of the criminal justice system under this view and involves difficult decisions regarding the form as well as the severity and certainty of the punishments imposed. The theory suggests that monetary sanctions should generally be preferred to non-monetary sanctions such as imprisonment (e.g. Polinsky and Shavell, 2007) and, given the form of the sanction, and ceteris paribus, an increase in the expected punishment (which is a function of severity and certainty of the punishment) will reduce individuals' propensity to engage in the wrongful act (general deterrence).1

In this paper, we provide a test of general deterrence by exploiting a natural experiment produced by an exogenous shift in the law governing the usage of checks in Turkey. In particular, we investigate whether the February 2012 amendments to the Turkish Check Law was a driver of the surge in the incidence of bad checks that occurred with similar timing. Prior to 2012, the act of issuing a bad check could and often did result in imprisonment, the duration of which depended on the value of the unpaid check. The amendments to the check law replaced prison sentence with civil sanctions such as fine payments, restrictions on the opening of check accounts, and prohibitions on the issuance of checkbooks for a number of years. This change implied a substantial reduction in the severity of punishment for issuing bad checks. We conjecture that this unprecedented change might have induced some check issuers to renege on their commitments, thereby leading to the observed rise in the incidence of bad checks.

Investigating the impact of the February 2012 change in the laws governing the usage of checks in Turkey is interesting for at least two reasons. First, by replacing imprisonment with monetary and administrative sanctions, the 2012 change removes the act of issuing of bad checks from the realm of criminal law and places it under that of civil law (decriminalization). This represents a rare natural experiment that allows the analysis of the effects of different types of legal sanctions. Since replacing imprisonment with monetary and administrative sanctions leads to a large reduction in the severity of punishments without a concomitant change in their certainty, the 2012 change also provides a unique opportunity to study the behavioral effects of changes in sanction severity. Second, studying the February 2012 law change is important from an economic policy perspective as well because checks have historically been a cornerstone of Turkish commercial life, utilized predominantly by merchants, traders, craftsmen, and artisans in their business transactions. Moreover, checks are one of the most widely used mediums of exchange within the commercial sector (particularly among privately-held small- and medium-sized enterprises, which constitute 99.8 percent of all firms): the economywide value of checks corresponds to roughly one third of do-

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1 See Harel (2012) and Fisher (2014) for reviews of the literature on the economic analysis of criminal law.
mestic output each year. This contrasts with the practices in most other economies where checks are also widely used by consumers in various market transactions. Equally importantly, checks are typically post-dated in Turkey, meaning that they serve not only as a means of payment but also as a credit instrument. Accordingly, a drastic change in laws governing the use of checks such as the one that occurred in February 2012 might have important implications for the health and stability of the business sector in the Turkish economy.

Our data on checks comes from the Interbank Check Clearing House of Turkey and is available at monthly frequency between January 2005 and March 2015. Figure 1 shows that during our sample period there have been two instances where the fraction of bad check counts (i.e. the number of bad checks divided by the total number of checks) surges. Figure 2 shows a similar time series pattern in the fraction of bad check values (i.e. the value of bad checks divided by the total value of checks). The first surge in the frequency of bad checks starts in the second half of 2008 and lasts until mid-2009 whereas the second begins around the middle of 2011 and lasts until the end of 2012. In terms of timing, while the former surge in bad checks coincides with the global financial crisis of 2008-09, the latter coincides with the European debt crisis of 2011, events both of which impacted on the Turkish economy. It is thus tempting to explain the two surges in the frequency of bad checks with the global financial crisis and the European debt crisis, respectively. However, two pieces of information make the latter part of this explanation suspect. First, variables comparable in nature to the fraction of bad checks such as the non-performing loans ratios do not show a similar rise during 2011-12. Second, this time period also saw an unprecedented shift in the laws governing the use of checks (the February 2012 amendments) that decriminalized the issuance of bad checks. Therefore, a main objective of the present paper is to investigate if the February 2012 change in the check law has an influence on the incidence of bad checks above and beyond the impacts potentially created by various macroeconomic events.

Our empirical analysis begins with investigating whether the time series for the fraction of bad checks presented in Figure 1 goes through any structural break between January 2005 and March 2015. Employing multiple break tests a la Perron and Qu (2007), we find that a structural break is present at each of the following four dates: August 2008 (upward change), March 2010 (downward change), October 2011 (upward change), and May 2013 (downward change). We next regress the fraction of bad checks on a number of key economywide economic and financial variables to find out if these breaks can be accounted for by the movements in the general economic environment. Our results show that while shifts in the economic environment (such as the global financial crisis and the European debt crisis) can account for the first surge in bad checks that begins around mid-2008, they cannot account for the second surge that begins around mid-2011. We then investigate if adding the proxies for the February 2012 change in the check law to our regression model can help account for the break in October 2011. We find that it does. We interpret this finding as evidence that the February 2012 legal change, which reduced the penalty for writing
bad checks, was a major driver of the surge in the fraction of bad checks that occurred with similar timing. In addition, we explore if the February 2012 legal change also induced people to issue bad checks of greater value but find no such evidence. This finding indicates that even though the legal change increased bad check issuance, it did not additionally lead to adverse selection problems in the form of people issuing bigger checks without an actual intention to repay. Finally, since the surge in bad checks in response to the legal change is followed by a return to pre-legal change levels in bad check incidence, we also analyze the speed with which economic agents adapt to the legal change. Our results indicate a fairly rapid adjustment: 90 percent of people adapt within 12 months following the change. Our main empirical findings are consistent with a model of general deterrence in which entrepreneurs issue checks to fund potential investment opportunities and where the decision to issue checks involves a trade-off between the expected return to the investment and the legally-determined expected cost of defaulting on a check.

One potential difficulty with our empirical analysis is choosing an appropriate proxy for the February 2012 legal change. Applied researchers typically rely on the dummy variable approach in which the dummy variable is equal to one for observations subject to the operation of the experiment and equal to zero otherwise. However, as Higgins and Johnson (2003) and White (2005) argue, in natural experiment contexts such as the one considered in this paper, the conditions required for the dummy variable approach to consistently estimate the effect of interest are generally extremely stringent. The main difficulty is that the dummy variable might be picking up effects that are contemporaneous but completely unrelated with the natural experiment in question. Therefore, we adopt a different approach and develop an alternative proxy that directly represents the February 2012 change in the check law. Specifically, we use the cumulative volume of web search queries from Google related to the February 2012 change such as “check law” and “bad/bounced checks” as a proxy for the legal change. The idea behind our approach is simple: Since the internet is now a major source of news and information for a large number of people, online activity at any moment in time can be used to gain insight into people’s current interests, concerns, and intentions.2 Thus, the volume of online activity related to the February 2012 legal change can be used as a measure of the number of people who are informed and concerned about this event in a given time period. People would search the internet, presumably, to understand what the legal change is about and to decide on the appropriate course of action based on that information. It is also important to note that because the public discussions about the February 2012 legal change started several months earlier, people began gathering information and adopting appropriate individual responses to the change in law before it actually took

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2 See, for example, Ettredge et al. (2005), Choi and Varian (2009a), or Goel et al. (2010). A rapidly growing number studies in economics in the past ten years have used web search query data for nowcasting and forecasting purposes. These studies have shown that search data can provide timely information on variables of interest ranging from macroeconomic variables such as unemployment rates (e.g. Choi and Varian, 2009b, and Askitas and Zimmermann, 2009), private consumption (e.g. Suhorj, 2010, and Vosen and Schmidt, 2011), consumer sentiment (e.g. Della-Penna and Huang, 2009, and Gürzür, Kılıç, and Osman, 2016), and inflation expectations (e.g. Guzman, 2011) to more disaggregated variables such as retail sales, property transactions, car registrations, and foreign trips (e.g. Chamberlain, 2010), automobile purchases (Carriere-Swallow and Labbe, 2013), and cinema admissions (Hand and Judge, 2012). To our knowledge, our paper is the first to use web search data to construct an indicator of a change in law.
effect. The fact that our Google-based proxy successfully captures this behavioral change provides another reason why it is a more appropriate measure of the legal change than a simple dummy variable.

Studies related to the deterrent effects of penal sanctions focus on the severity as well as the certainty of different forms of punishment and provide mixed evidence regarding the effectiveness of these two aspects of punishment and their interaction. While the method of punishment can be of various forms, we take the studies on imprisonment as a comparison point since the relevant policy change in our context involves replacing imprisonment with monetary and administrative fines. Studies like Spelman (1994), Levitt (1996), Spelman (2000), and Liedka, Piehl, and Useem (2006) argue that there is a negative relation between the rate of imprisonment and aggregate crime rates.3 Wellford, Pepper, and Petrie (2005) find a deterrent effect of Massachusetts gun law introducing one year prison sentence for unlawful carriage. Using the Collective Clemency Bill example from Italy, Drago, Galbiati, and Vertova (2009) find that an increase in the length of the expected sentence for conditionally released former inmates decreases the likelihood of recidivism. Weisburd et al. (2008) find that problem-oriented policing is effective in reducing crime and disorder, although the effect is fairly modest. Lee and McCrary (2009) focus on young offenders and observe that there is no decline in offending rates around the time they turn 18, the age which implies legal treatment as adults and therefore more severe sentences. Studies like Nagin (2013) and Durlauf and Nagin (2011), on the other hand, argue that there is more consistent evidence on the effectiveness of the certainty rather than the severity of punishment.

Our paper contributes to this literature by providing evidence of deterrence from a natural experiment in which an exogenous shift in legislation alters expected sanctions. The natural experiment we consider combines a number of features rarely found in the extant empirical literature.4 First, it involves both a change in the form (from imprisonment to monetary and administrative) and severity of punishments without a simultaneous change in certainty. Second, while most studies test general deterrence by analyzing how crime rates are affected in response to an increase in sanctions, we analyze the effects of a reduction in sanctions, thereby providing evidence that deterrence works both ways as suggested by theory. Third, unlike most tests of deterrence which focus on crimes such as theft, robbery, assault, homicide, etc., our natural experiment involves offenses related to a purely economic variable, checks, thereby bringing evidence from a setting where the economic approach to law would be least controversial. Finally, while most studies of deterrence focus on advanced economies, our paper brings an example from a developing economy, thus providing evidence that the theory of deterrence can be used to study criminal behavior in less advanced economies as well.

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3 See Donohue (2009) for detailed information on and comparison of the estimates of the elasticity of crime with respect to incarceration.

4 One main exception is Babaoglu and Wulf (2015), who, like us, focus on the effects of the February 2012 change in the check law in Turkey. However, our paper differs from their paper in many respects including in scope, data used, methods of analysis, and range of findings. As such, our paper should be viewed as complementing and extending theirs.
The remainder of the paper is organized as follows. Section 2 provides a brief history of Turkish Check Law. Section 3 describes the data. Section 4 presents the empirical analyses and results. Section 5 presents a simple model of decriminalization of bad check issuance. Section 6 concludes.

2. A Brief History of Turkish Check Law

In this section, we provide a brief history of the regulations governing the usage of checks in Turkey, with a particular emphasis on the most recent changes. Demir (2013) and Babaoglu and Wulf (2015) provide detailed accounts of the evolution of these regulations. These papers also provide excellent discussions of the socio-political discourse leading up to the decriminalization of the issuance of bad checks in 2012. Our summary draws extensively on these papers.

Regulations governing the use of checks in business transactions were historically specified in the Turkish Commercial Code under the section “Exchange Bills”. This law regarded checks as a means of payment but did not impose any legal penalty for issuing bad checks. As the use of checks became more common and the need for security in business transactions increased, it became necessary to strengthen existing regulations. An important step in this direction was the introduction of Law No. 3167, which came into effect on May 19, 1985. Under this law, issuers of bad checks were subject to both administrative fines and a prison sentence of 1 to 5 years. Since issuing a bad check was regarded as a criminal offense, it was the duty of the state to initiate the relevant legal proceedings following the bouncing of a check. To further enhance trust in checks, Law No. 3167 was amended several times in the following years. Nevertheless, there was widespread perception that the law resulted in unreasonably long legal proceedings and had no significant deterrent effect despite the relatively harsh imprisonment terms. Check Law No. 5941, which was published in the Official Gazette on December 20, 2009, was a first step in mitigating these complaints. The issuer of a bad check could now escape going to prison as long as he paid a certain court-ordered monetary fine within a specified time frame. However, issuing a bad check was still considered a criminal act and trials were held at criminal rather than civil courts. Law No. 5941, therefore, only partially decriminalized the issuance of bad checks. The same law also increased the liabilities of commercial banks for bad checks and required them to conduct more detailed examination of clients’ credit history before opening check accounts and issuing checkbooks.

The most recent and arguably the most important change in the regulations governing the use of checks came on February 03, 2012 with the Law No. 6273. This law amended the Law No. 5941 and abolished prison sentence altogether, thereby fully decriminalizing the issuance of bad checks. Issuers of bad checks would now be subject to only monetary fines and administrative penalties. Accordingly, trials were now to be held at civil rather than criminal courts. Moreover, proceedings would begin only after a complaint is filed by the check holder at the prosecution offices within a specified time frame after the check bounced at the bank. Administrative penalties for offenders included prohibitions on the opening of check accounts and the using of checks in business transactions for several years. These restrictions could be lifted by the prosecutors if the full amount of the check plus a fine was paid by the offender in a timely
manner. At the same time, Law No. 6273 increased the responsibilities of commercial banks regarding the handling of checks. In particular, banks’ minimum liability for each bouncing check was nearly doubled, their client screening requirements when opening check accounts and issuing checkbooks were increased, and keeping check issuers’ financial records as well as reporting those records to the Central Bank of the Republic of Turkey became mandatory.

One additional piece of information can shed light on why the writing of bad checks was punishable under criminal law until the most recent legal reform in 2012. In particular, differently from the practices regarding check use in most countries, checks in Turkey are almost always post-dated. This means that the check usually specifies a future redemption date, which is determined by an informal agreement between the issuer and the holder of the check. As such, checks serve not only as a means of payment but also as a financial instrument that enables borrowing and lending. This standard historical practice is interesting given that the Turkish Commercial Code (Articles 780-823) defines checks as a means of payment, not a credit instrument, and states that a check is payable at sight. This dual function of checks as both a payment and credit instrument implies that ensuring the reliability of checks was and still is critical in ensuring the health of the commercial sector.

Despite the consensus on ensuring the status of the check as a reliable financial instrument, choosing the appropriate type of sanction for issuing bad checks has long been a controversial issue in Turkey. On the one hand, opponents of decriminalization viewed the issuance of bad checks as a serious fraud and crime which, unless punished severely, could potentially destabilize the economy. Given the widespread use of checks, proponents of this view argued that the health and stability of the commercial sector depended critically on the reputation of the check as a reliable payment and credit instrument. In their view, this could be best achieved by sending the issuers of bad checks to prison. Proponents of decriminalization, on the other hand, argued that economic offenses should be punished by economic sanctions. They also argued that sending the offender to prison was counterproductive because it made repaying the outstanding debt more difficult or even impossible. These complaints became particularly forceful during the global financial crisis of 2008-2009, which sent the number of bad checks skyrocketing and caused many honest but unlucky people to go to jail due an inability to honor their checks. The surge in personal and familial tragedies during the crisis turned public opinion in favor of decriminalization. As a result, bad check issuance was first partially decriminalized in December 2009 and then fully decriminalized in February 2012.

3. Data

In the empirical analyses that follow, we investigate whether the surge in the share of bad checks in total checks (our dependent variable) beginning in late 2011 can be accounted for by the February 2012 change in the Turkish Check Law (our main independent variable).

Our data on the fraction of bad checks comes from the Interbank Check Clearing House and is available at monthly frequency from January 2005. This data source keeps record of “swap checks”, i.e. checks
that are issued by a commercial bank and presented by the last check holder to a commercial bank that is different from the issuing bank. Hence, it does not provide information on checks that are issued by and ultimately returned to the same bank for redemption. The complete data that includes information on both swap checks and same-bank checks can in principle be obtained from the Banks Association of Turkey. Unfortunately, however, this data source does not provide monthly data prior to 2009, thereby making it impossible to observe also the pattern leading up to the global financial crisis of 2008-2009, which is necessary for our analyses. Nevertheless, the fact that the overwhelming majority of checks are swap checks implies that we lose very little by using the Interbank Check Clearing House data rather than the Banks Association of Turkey data. This can be seen from Figure 3 and Figure 4 which show that both the total number of checks and the fraction of bad checks are very similar across the two data sources.5

For reasons we explain in the next section, we employ two alternative variables that proxy for the February 2012 amendments to the check law in Turkey rather than using the legal change itself. Our first proxy is the number of Google searches related to the February 2012 legal amendments and is obtained from the Google Trend service. Our second proxy is the number of web links containing legal-amendment-related terms and is obtained from Google search engine.

We also use a number of macroeconomic and financial variables to control for effects not captured by our proxies for the legal change. While the data on the industrial production index, Borsa Istanbul (BIST) 100 index, consumer price index, real sector confidence index, and total number of protested bills are taken from the Central Bank of the Republic of Turkey, the data on non-performing loans is taken from the Banks Association of Turkey.6 All of our data are computed at the monthly frequency and run from January 2005 to March 2015.

4. Empirical Methodology and Results

In this section, we conduct a formal empirical investigation of the legal and economic determinants of the movements in the frequency of bad checks in Turkey during 2005-2015. We also provide a quantitative measure of the speed with which economic agents adapt to the new environment produced by the February 2012 change in the check law.

5 The Interbank Check Clearing House data on Figure 3 starts from 2008 whereas the Interbank Check Clearing House data on Figure 4 starts from 2005. This is because the Interbank Check Clearing House does not reveal check volumes before 2008 but only the fraction of bad checks in total check figures.

6 The data on the real sector confidence index shows discontinuity from December 2006 to January 2007 due to a change in its collection method. The two data are merged by using the by using the growth rate of CNBC-E consumer confidence index from December 2006 to January 2007.
4.1 Testing for Structural Breaks in the Fraction of Bad Checks

To test for structural breaks in the fraction of bad check counts, we use the equation

\[ y_t = c^n + \varepsilon_t, \]  

where \( y_t \) denotes the fraction of bad check counts in the economy (i.e. the ratio of the number of bad checks to the total number of checks), \( c \) is a constant term, and \( \varepsilon_t \) is the error term. A break in the data would be captured by a statistically significant change in the value of the constant term \( c \). We allow for the possibility of multiple breaks and let \( c^n \) denote the value of the constant term in regime \( n \). With \( m \) break dates, \([T^1, ..., T^m]\), there are \( m + 1 \) regimes in the data and hence \( m + 1 \) different values for \( c^n \).

Testing for structural breaks entails splitting the data from possible break points and checking if conducting ordinary least squares (OLS) on the sub-samples separately yields a significantly better fit to the data than conducting OLS on the whole sample at once. The most common such test is the well-known Chow test, which tests whether a data series has a break at a given date. However, it is often the case that the break date is unknown to the researcher. In such cases, a more advanced test called the Quandt Likelihood Ratio (QLR) test (also known as the supremum test) can be used to identify the unknown break date endogenously from the data. Originally proposed by Quandt (1958, 1960) and further developed by Andrews (1993), the standard QLR procedure tests, for any given date, the null hypothesis that there is no structural break against the alternative hypothesis that there is a structural break. To this end, it calculates the value of the Chow statistic at each possible break date and then determines the (unique) date at which the value of the Chow statistic attains a maximum. The null hypothesis is rejected in favor of the alternative at the date the value of the Chow statistic attains a maximum if the value of this statistic also exceeds a critical value associated with a prespecified significance level.

The downside of the QLR test is that it has power only if there is a single unknown break under the alternative hypothesis. In cases where there are multiple possible unknown breaks in the data, the standard version of this test is no longer directly applicable. In such cases, one can in principle use single break tests such as the QLR test sequentially to consistently estimate all unknown break dates (Bai, 1997; Bai and Perron, 1998, 2003). However, it is possible to get more precise estimates of the break dates and to increase the rate of convergence to the break dates using methods that explicitly take into account the presence of multiple unknown breaks in the data. A well-known such method is that of Perron and Qu (2007) and it is the one we use in this paper. Following convention, we let the minimum segment of the data between two break dates be at least 15 percent of the data.

Results from applying the Perron and Qu (2007) method to our data in accordance with Equation (1) are displayed in Figure 5. The figure shows that there are four structural breaks and accordingly five dif-

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7 Regime \( n \) corresponds to the time interval \([T^{n-1} + 1, T^n]\) for \( n = 2, 3, ..., m \), whereas regime 1 and regime \( m + 1 \) correspond, respectively, to the intervals \([T_0, T^1]\) and \([T^m + 1, T_1]\), where \( T_0 \) is the date at which our data sample begins and \( T_1 \) is the date at which the sample ends.
ferent regimes in the data. The first break occurs in August 2008 and indicates an increase in (the unconditional mean of) the fraction of bad checks in the economy. This is followed by a sharp fall in March 2010, which seems to have permanently lowered the fraction of bad checks. The third and fourth breaks occur in October 2011 (upward change) and May 2013 (downward change) and both are smaller compared to the earlier two breaks.8

[Insert Figure 5 about here]

We also check for the stationarity of the fraction of bad checks series. The fact that our data series contains structural breaks implies that we cannot directly apply the usual unit root tests. This is because, as Perron (1989) has shown, in the presence of structural breaks, even if the data series follows a (trend) stationary process with a break in time, the unit root tests will reveal it as non-stationary. Accordingly, we first account for the breaks in the data series and then test for stationarity using the Dickey-Fuller test. Results confirm the stationarity of the data.9

4.2 Can the shifts in the economic environment account for the breaks?

We next explore if the structural breaks in the fraction of bad check counts shown on Figure 5 can be accounted for by variables that represent the state of the economic environment. If so, then the breaks should disappear once we control for the economic environment. To this end, we use the equation

\[ y_t = c + \alpha y_{t-1} + \beta X_t + \epsilon_t, \]

where \( y_{t-1} \) is the lagged value of \( y_t \), \( X \) is a vector of variables representing the state of the economic environment, \( \alpha \) and (the vector) \( \beta \) are parameters, and \( \epsilon_t \) is the error term. We include \( y_{t-1} \) to account for possible autocorrelation in the data and to control for any other variable that we may fail to include in the regression equation. The variables included in the vector \( X \), in turn, are described below.

**Industrial production index:** This variable is an indicator of the monthly economic activity in the economy. A higher level of the industrial production index reflects a stronger economy, which is likely to be associated

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8 Another interesting observation about our data is that the fraction of bad checks appears to have fallen to a permanently lower level following the global financial crisis of 2008-09: while the fraction of bad checks was on average around 5 percent each month before the crisis, it dropped to around 3.5 percent after the crisis. We conjecture that the surge in bad checks and the associated financial distress drove weaker check issuers out of the market (either due to bankruptcy or imprisonment), thereby improving the quality of check issuers that remain. Another factor that might have contributed to this change is the partial decriminalization of bad checks during late 2009. In particular, partial decriminalization might have signaled to market participants that full decriminalization is under way and this might have motivated businessmen to become more careful than before when accepting checks. The overall effect of these two factors would be a fall in the reputation of checks and a consequent decline in their popularity as a payment and debt instrument. Data appears to be consistent with this view, as the monthly number of checks appears to have fallen permanently from an average of about 2 million before the crisis to about 1.5 million after the crisis.

9 In principle, one can test for unit roots and structural breaks simultaneously; for instance, by using unit root tests that allow break(s) under both the null and alternative hypotheses (see Lee and Strazicich, 2003, 2004). However, these tests have power only when there are at most two break(s) in the data, whereas our data series has four breaks.
with a lower probability of checks being bounced when presented to a bank for redemption. Moreover, our preliminary regression analysis indicates that not only the current value of this variable but also its first, second, third, and fourth lags are able to explain the bad check data. This result might reflect the fact that, in Turkey, checks are typically post-dated. In particular, there might be a lag between the time an economic downturn pushes firms into financial distress and the time the checks issued by such firms come due.

**BIST 100 index:** This is the stock market value of the top 100 firms in Borsa Istanbul - the main stock exchange in Turkey. This variable is another indicator of economic activity in the economy and we include it in our models to complement the industrial production index.

**Real sector confidence index:** Based on the Business Tendency Survey of the Central Bank of the Republic of Turkey, this index tracks on a monthly basis the views of real sector representatives about the general economic outlook in the short term. A higher level of the index is likely to be associated with a lower incidence of bad checks.

**Number of protested bills:** Although not as widely-used as checks, bills are an alternative form of payment to checks in Turkey. Like checks, bills are usually post-dated in practice and hence serve as a debt instrument. Unlike the case for checks, however, failing to honor a bill has never been a criminal matter in Turkey. We include the (monthly) number of protested bills in our models because bills are a close substitute for checks. The idea is that while a change in the state of the economy would affect both the number of bad checks and the number of protested bills, a change in the law governing check usage would impact on the former but not the latter.

**Ratio of non-performing loans:** As noted earlier, checks in Turkish business practice are not merely a vehicle for making payments; they are often used as a means of borrowing. As such, there is considerable degree of substitutability between checks and more conventional forms of borrowing arrangements, such as bank loans. To control for this, we also include the (monthly) rate of non-performing bank loans in our models. Again, we would expect that a shift in the state of the economy would influence the incidence of both bad checks and non-performing loans, but that a change in the check law would impact on the former but not the latter.

Figure 6 presents the results from estimating the model in Equation (2). Since our multiple break tests now find only one structural break in the data, it is sufficient to report the (single break) QLR test statistics. Recall that the dates at which the value of the QLR statistic exceeds a chosen critical value are possible break dates and that the date at which the QLR statistic achieves a maximum is the most likely break point. Accordingly, the results shown in Figure 6 indicate that there is a break in the fraction of bad

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10 Ideally, we would want to use the “fraction” rather than the “number” of protested bills; however, we are unable to calculate this statistic since data on the total number of bills is not collected by the authorities.
checks series between early 2011 and late 2012 (significant at the 5 percent level) and that this break most likely occurs in December 2011. Note that December 2011 is very close in timing to October 2011, one of the four break dates identified at the beginning of Section 4.1. By contrast, Figure 6 provides no evidence of the existence of a break during the global financial crisis of 2008-9. Therefore, our findings suggest that while the shifts in the proxies for the state of the general economic environment can account for the first surge in bad checks that begins around mid-2008, they cannot account for the second one that begins around mid-2011.

[Insert Figure 6 about here]

4.3 Can the change in the check law account for the break in December 2011?

We have shown in the preceding section that, once we control for the state of the economic environment, the fraction of bad checks series goes through only a single structural break during our sample period and that this break most likely occurs in December 2011. We now want to find out if this break is causally related to the legal change that occurred in February 2012. To this end, we modify Equation (2) as

\[ y_t = c^n + ay_{t-1} + \beta X_t + \gamma LC + \varepsilon_t, \]  

(3)

where \( LC \) (short for Legal Change) is a proxy variable for the February 2012 amendments to the check law that abolished imprisonment for writing bad checks. The only new element in this equation with respect to Equation (2) is the inclusion of the variable \( LC \). Our goal is to find out whether, after controlling for the possible effect of the legal change, the break in the data in December 2011 still remains or not.

What would constitute a good proxy for the legal change? Perhaps the most obvious candidate would be a dummy variable that is equal to one after the introduction of the legal change and equal to zero otherwise. In unreported results, we find that using a dummy variable that proxies for the legal change can indeed account for the December 2011 break in the data, as the break disappears once we include the dummy variable in our model. However, as noted earlier, it is possible that the dummy variable is capturing the effect of a completely unrelated event that occurs with similar timing and this casts doubt on the reliability of the result. Therefore, we also use web search data to construct proxies that directly represent the February 2012 change in the check law. The two alternative proxies we construct, \( LC^1 \) and \( LC^2 \), are respectively (i) the volume of web searches related to the February 2012 legal change and (ii) the volume of web links containing keywords related to the February 2012 legal change.

4.3.1 Constructing the first proxy for February 2012 legal change

Our first and preferred proxy, \( LC^1 \), is based on Google Trends. Although there exists a host of web search engines (such as Bing, Ask Jeeves, and Yandex), Google is currently the only one with a publicly accessible interface that allows researchers to obtain the popularity patterns of a chosen search term. As a result, Google Trends is the most widely used web search data source in studies of involving nowcasting and forecasting. In addition, according to the internet marketing consulting firm Return on Now
Google is the dominant web search engine in Turkey, representing 96 percent of the market. Using Google Trends, therefore, allows us to cover the largest possible sample of web users in Turkey while constructing our web-based proxy for the legal change.

The Google Trends service provides a time series index of the volume of queries users enter into Google in a given geographic area and is available at weekly frequency. The index reflects the “popularity” of the selected search queries in the region and time period chosen by the user. The popularity of searches is then normalized so that they take values between 0 and 100, with higher numbers indicating higher popularity. This allows users to track the popularity of search queries over time in a consistent manner.

Since our analyses require monthly data, we aggregate weekly data to obtain a monthly series.

Using Google Trend data has advantages and disadvantages. On the plus side, by virtue of providing a time series index (rather than raw data), Google Trend possibly eliminates both the natural time trend—which would arise because of growing internet usage over time—and the seasonality in the data—which would arise due to changes in the frequency of internet usage throughout the course of a year. On the negative side, it does not allow us to observe the actual number of searches; however, this is not a problem in our case since we are not interested in the coefficients on the independent variables but rather the explanatory power of these variables.

A critical step in constructing our proxy is choosing appropriate search keywords. To this end, we consider keywords related with the legal change such as “check law” and “bad/bounced check law” as well as those related with the legal penalties for writing a bad check such as “imprisonment/penalties for bad/bounced checks”. Among these keywords, we exclude those that produce little or no search result and those whose search volume is very small in comparison to that of the term with the highest search volume, which, in our case, is “check law”. This leaves us with two main keywords, namely “check law” and “bad/bounced check”. Figure 7 displays the time series graphs for each of these search terms obtained from Google Trends. The figure also displays the graph obtained by aggregating the data in the three individual keyword graphs; and this is the series we use to construct our proxy for the February 2012 legal change. Note that we have two different graphs for “check law”—panels 1 and 2—because there are two different Turkish words that correspond to the English word “law”, namely “yasa” and “kanun”. Since both words generate substantial search volumes, we include the graphs for both words in Figure 7.

Figures 7 shows that there are two main dates at which the search volumes make a peak: December 2009 and January 2012. This is perhaps most clearly visible in Panel 4 of Figure 7, which shows the time

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11 See Choi and Varian (2009a) and Gürgür, Kılınç, and Orman (2016) for more on this point.

12 Google Trend allows one to search multiple keywords simultaneously. In this case, the keyword with the highest search results is set to 100 and others are indexed accordingly, thereby allowing one to compare the relative frequencies of different search items. We should note, however, that our results are not sensitive to the exclusion/inclusion of keywords with low relative search frequencies. This most likely reflects the fact that these keywords have time series patterns that are very similar to those with the highest search frequencies shown on Figure 7.
series obtained by aggregating the individual time series in the remaining three panels. Observe that these peak dates coincide (almost) exactly with the December 2009 and February 2012 changes in the check law, indicating that web keyword search volumes can in fact capture the actual changes in law.

The next step in constructing our proxy variable is that we take the frequency distribution of search queries in Panel 4 of Figure 7 and create a cumulative distribution of search queries by summing the original series over time. In particular, letting $G_t$ denote the volume of search queries at time $t$, we construct the series

$$LC_t = G_t + G_{t-1} + G_{t-2} + \cdots + G_T$$

where $LC_t$, as introduced earlier, is our proxy for the change in the check law and $T$ is a starting date to be chosen. The idea behind this formulation is our intuition that the total number of people informed/concerned about the legal change by time $t$ is a better proxy for the impact of the legal change than the number of people informed about the change specifically at time $t$.

The final step is to choose $T$. Recall that the data in Figure 7 has two peaks, one coinciding with the legal change in December 2009 and the other with the change in February 2012. Because our primary focus is the February 2012 legal change, in constructing our proxy variable, we must include only the searches that are related with this particular change and remove those that are likely to be unrelated. A visual inspection of the data in Figure 7 suggests June-July 2011 is a natural cutoff point as the frequency of search queries falls down to minimal levels; in some cases, it falls all the way to zero. We therefore set $T =$ August 2011 and assume that only the search queries beginning with this date are related with the February 2012 legal change.14

Having constructed our proxy variable, $LC$, we are now ready to estimate the model in Equation (3). Figure 8 presents the results from this estimation. The results show that the QLR statistics never exceed the critical value associated with the 5 percent significance level, implying that the fraction of bad check series no longer shows a structural break during our sample period. Thus, once we include our proxy for the February 2012 legal change in an equation that otherwise includes only variables proxying for the state of the economic environment, the February 2012 break in Figure 6 disappears as well. We, therefore, conclude that the February 2012 break in the fraction of bad checks series cannot be solely accounted for by the movements in the economic environment; the February 2012 change in the check law that decriminalized bad check writing must also be taken into account.

At this point, it might be helpful to say a few words about the first of the two peaks in Figure 7, namely the peak in December 2009. Recall that the timing of this peak coincides perfectly with the change

\[\text{Insert Figure 8 about here}\]

13 This choice of August 2011 as the cutoff date is also supported by our finding that the number of web links to our main keywords (produced by Google search engine) also falls to minimal levels in June-July 2011.

14 In unreported results, we find that our main conclusions are not sensitive to the choice of the cutoff date, $T$. 
in the check law that took place in the same month that partially decriminalized the writing of bad checks. Our proxy variable, thus, accurately captures people’s interest about this law change as reflected in relevant web search volumes shown in Figure 7. It is important to emphasize that the December 2009 legal change was motivated, among other things, by a desire to contain the adverse effects of the global financial crisis of 2008-2009 on the business sector. As Figure 1 shows, there was an explosion of bad checks during the crisis, with a peak in the first quarter of 2009. Hence, in contrast with the full decriminalization of bad check writing in 2012, the 2009 law change was a response to, as opposed to being a driver of, the surge in bad checks. Moreover, as we have shown earlier, the changes in data that occur around 2008-09 can be accounted for by variables representing the state of the economic environment.

4.3.2 Constructing the second proxy for February 2012 legal change

The second proxy variable, \( LC^2 \), we consider is the number of web links containing information about the February 2012 change in law. To this end, we enter the keywords “check law” and “bad/bounced check” into Google web search engine and restrict the search period to a particular month. Repeating this process for every month between January 2005 and March 2015 provides us with the monthly time series to be used in our analysis.

Figure 9 presents plots of the time series associated with each keyword as well as the plot obtained by aggregating individual time series. In what follows, it is sufficient to focus on the aggregated time series displayed in the final panel of Figure 9, as this series is the one we use in constructing our proxy variable. What’s clear from this figure is that there is a surge in the volume of web links in January 2012, just before the 2012 change in the check law. Although there is also a rise in web link volumes during late 2009, it is not as evident as it was in Figure 7. Note also that the time series displays an obvious time trend. This reflects the fact that, unlike Google Trends, the Google search engine provides the absolute volume of relevant entries, which increases over time due to growing internet usage. In order to obtain a series that will allow a meaningful comparison of the frequency of a given keyword over time, we remove the time trend from the data. We find that our data can be appropriately detrended by fitting a polynomial of degree one.

[Insert Figure 9 about here]

In constructing our proxy variable, we follow the steps described in the previous subsection. Specifically, we take the detrended data series, convert it to a series that provides the cumulative volume of web links at any given date, and choose a starting date \( T \) so that unrelated web links are excluded.

Figure 10 presents the results from estimating the model in Equation (3) with our new proxy variable, \( LC^2 \). As was the case in Figure 8, the QLR statistics never exceed the critical value, implying that the fraction of bad check series no longer shows a structural break during our sample period. However, differently from the previous case, this result obtains significance only at the 10 percent level. Moreover, our results are also more sensitive to the choice of the cutoff date, \( T \), in this case. Fortunately, though, changing \( T \) always preserves significance at the the 10 percent level and, in some cases, leads results to be significant
at or around the 5 percent level. We, therefore, arrive at the same conclusion as in the previous section, albeit with a somewhat lower level of confidence. Specifically, we again conclude that the December 2011 break in the fraction of bad checks series can be completely explained only when the February 2012 legal change and the changes in the economic environment are taken into account simultaneously.

[Insert Figure 10 about here]

The structural break approach is a powerful method to investigate if and when breaks occur in the data. To provide also a sense of the statistical importance of our independent variables, we present in Table 1 the results from the regression of the fraction of bad checks on our main independent variables. The only difference between the two columns in Table 1 is the definition of the proxy variable for the 2012 legal change ($LC^1$ versus $LC^2$). In both columns, the economic/financial independent variables with the highest statistical significance are the Borsa Istanbul 100 Index, the number of protested bills, and the non-performing loans ratio. The industrial production index is significant at 5 percent in one of the regressions and at 10 percent in the other. The real sector confidence index is insignificant in both regressions. Moreover, consistent with expectations, the industrial production index and the Borsa Istanbul 100 index are negatively related with the fraction of bad checks whereas the number of protested bills and the non-performing loans ratios are positively related. Most importantly, our proxy variables for the legal amendment ($LC^1$ and $LC^2$) attain highly statistically significant coefficients with the expected positive sign in both regressions. Finally, the $R^2$'s in both regressions are very high, indicating that our independent variables explain nearly 90 percent of the variation in the fraction of bad checks.

4.4 Testing Structural Changes in the Average Value of Bad Checks

Thus far, we have examined the determinants of the structural breaks in the fraction of bad check counts (the number of bad checks as a share of the total number of checks) shown on Figure 1. Our primary focus has been the break occurring during late 2011. We have shown that this break, unlike the others, can only be fully explained when the February 2012 change in the check law is also taken into account.

We next consider the fraction of bad check values, that is, the Turkish Lira value of bad checks as a share of the Turkish Lira value of all checks, presented in Figure 2. A comparison of Figure 1 and Figure 2 indicates that the two time-series display very similar patterns. This raises the question: Are the movements in the value series in Figure 2, and in particular the movements during late 2011, simply a reflection of the movements in the count series in Figure 1? Or, is there also a change in the average value of bad checks (relative to the value of all checks)? The average value of bad checks can be expected to change for at least two reasons. On the one hand, moral hazard on the part of check issuers might motivate them to issue checks of greater value. For if a check issuer has no intention of honoring his check, it is optimal for him to issue checks of maximal possible value. This effect would tend to increase the average value of bad checks. On the other hand, expecting this sort of behavior from check issuers, check holders might decide to put a cap on the value of checks they accept. This would reduce the average value of bad checks. The
net effect on the value of the average bad check will thus depend on the interplay between these two theoretical forces, the answer to which can only be determined empirically.\textsuperscript{15}

We can use the following identities to begin answering this question:

\[ \text{Value of checks} \equiv \text{Number of checks} \times \text{Average check value}, \]

and

\[ \text{Value of bad checks} \equiv \text{Number of bad checks} \times \text{Average bad check value}. \]

Dividing the second equation by the first, we obtain

\[
\frac{\text{Value of bad checks}}{\text{Value of checks}} = \frac{\text{Number of bad checks}}{\text{Number of checks}} \times \frac{\text{Average bad check value}}{\text{Average check value}}.
\]

Observe that Figure 2 plots the left hand-side of this equation whereas Figure 1 plots the first term on the right hand-side. This equation shows that a change in the fraction of bad check values must be due to a change either in the fraction of bad check counts or in the average check value ratio or both. We already know from previous sections that there is a structural break in the first term on the right hand-side of this equation during late 2011 that can only be fully explained by including the February legal change in our model. We now want to find out if a structural break is also present in the average check value ratio, the second term on the right hand-side of the equation. To this end, we estimate the following equation:

\[
v_t = c^n + \alpha v_{t-1} + \beta Z_t' + \epsilon_t, \quad (4)
\]

where \(v\) is the average bad check value and \(Z\) is the vector of variables representing the state of the economic environment including the industrial production index and its first four lags, BIST 100 index, real sector confidence index, average value of protested bills, value of non-performing loans, average check value, and consumer price index. Differently from previous regression equations, we include the price index since our dependent variable is now a nominal variable and include average check value to control for the general trend in check values. Our analysis covers the period after January 2008 as the data on the total number of checks is available only after this date.

Figure 11 presents the break statistics from estimating Equation (4). The results show that there is no break in the average bad check value in or around December 2011.\textsuperscript{16} This finding suggests that any movement in the average bad check value in or around late 2011 can be entirely accounted for by the movements in the state of the economic environment. This, in turn, implies that the movements in the bad check value ratio series during late 2011 in Figure 2 simply reflect movements in the count series in Figure 1. We can, therefore, conclude that even though the February 2012 change in check law led to an

\textsuperscript{15} It is important to note that unlike the case where the check issuer is honest but illiquid at the time of the check due date, issuing a check with no intention of paying amounts to fraud. Therefore, we want to find out if decriminalizing one type of crime – issuance of bad checks – leads to the emergence of other types of crime – fraud.

\textsuperscript{16} The only break in the data occurs in June 2013 but this has nothing to do with the February 2012 legal change.
increase in the incidence of bad checks (Section 4.3), it did not further worsen the business climate by subjecting check holders to increased levels of fraud in the form of unpaid checks of greater value.\footnote{We should note that part of the increase in the incidence of bad checks can still be due to increased levels of fraud. However, this type of fraud does not increase the average value of bad checks and is arguably less of a problem. Moreover, it is impossible to empirically distinguish between honest delinquencies due to illiquidity of the check issuer and nonpayments due to fraud when there is no change in the average value of bad checks.}

[Insert Figure 11 about here]

### 4.5 Adapting to the new check law

Figure 5 shows that the rise in the fraction of bad check counts induced by the February 2012 change in check law continues until the end of 2012. The fraction of bad checks subsequently declines and then stabilizes around 2.5-3.0 percent, indicating that the effect of the change in the check law is not permanent. We interpret this as evidence that people adapt to the change brought about by the February 2012 amendments to the check law. But how does this adaptation take place?

In our opinion, checks lost (at least some of) their previous reputation as a solid means of credit/payment following the February 2012 legal change (which considerably reduced the severity of penalties for issuing a bad check) and, as a result, were not used in business transactions as frequently as before. On the one hand, check holders likely became more cautious about accepting payment by checks. On the other, in part induced by the rules and regulations brought about by the February 2012 change in the check law, commercial banks increased their screening efforts and raised their standards for opening check accounts and issuing checkbooks to clients. The behavioral changes on the part of banks and check holders likely drove many of the check issuers who have failed or are likely to fail to honor their payments out of the market. The resultant improvement in the pool of check issuers, in turn, led to a gradual reduction in the incidence of bad checks.

One development that might have helped check holders and banks adjust to the change in the check law (and hence reduce the frequency of bad checks in the economy) is possibly the increased efforts of the Credit Registration Bureau in 2012 to monitor risk in credit transactions, including checks. Specifically, the Bureau introduced a check reporting system in April 2012 for the specific purpose of increasing the reliability of checks in the business life. The system provides detailed information on the past check payment behavior of check issuers so as to aid check holders in making a sound decision on whether or not to accept a check and to aid banks in deciding whether to issue a checkbook to a client.\footnote{The system provides information on banks where the client's check account is available, number of the checks submitted since 2007, number and amounts of the checks paid at sight, number and amounts of the checks after 2009 which were bounced and paid on a later date, date of the first submitted check and the date of the first endorsed check, date of the last check submitted and endorsed, number and amounts of the checks paid and endorsed during the last 1, 3 and 12 months period, and information on the list of up to 50 endorsed checks.} To see if we can capture the Credit Registration Bureau effect empirically, we reestimated Equation (3) while including on the right hand-side a dummy variable that is equal to one starting in April 2012 and equal to zero other-
wise. However, the coefficient on the dummy variable was not statistically significant. Therefore, although the increased efforts of the Credit Registration Bureau may have been helpful, this was not the sole or even the most significant determinant of how individuals and banks adapt to the February 2012 change in the check law.\footnote{Babaoglu and Wulf (2015) find that the establishment of the Bank Association of Turkey Risk Center in June 2013 contributed to a reduction in the frequency of bad checks. Much like the Credit Registration Bureau, the Risk Center gathers and disseminates information regarding risk in all types of credit transactions. To see if this is the case, we included in Equation (3) a dummy variable that is equal to one starting in June 2013 and equal to zero otherwise. Unlike Babaoglu and Wulf (2015), we found the coefficient on the dummy variable to be statistically insignificant. Since our empirical methodology is very different from theirs, the results across the two papers are not directly comparable. However, in our view, it is not very reasonable to expect the establishment of the Risk Center to have any major effect on the fall in the frequency of bad checks. For one, the fall in the frequency of bad checks precedes the establishment of the Risk center by approximately seven months (December 2012 versus June 2013). In addition, the functions of the Risk Center were not brand new; they were historically conducted by the Central Bank of the Republic of Turkey and, as noted earlier, the Credit Registration Bureau also provided similar services beginning in April 2012.}

How quickly do people adapt to the change in check law? The answer to this question can be of interest to policy makers and academics alike, as it can provide insights into the socioeconomic costs of implementing a change in policy. If banks and check holders perfect their screening skills sufficiently quickly, then the change in law need not result in a rise in the incidence of bad checks. However, we know from Figure 1 that there is a substantial rise in the number of bad checks between mid-2011 and end-2012, indicating that it did in fact take time for people to adjust to the new situation. To answer this question empirically, it is convenient to view the change in the check law as a temporary shock to the economy and then calculate the memory of this shock. To this end, we assume that each month a given fraction, $1 - \rho$, of people adapt to the change in check law. Under this assumption, the memory of the shock is given by $\rho$, the fraction of people who have not yet adapted to the change in check law. As before, we use Google Trend search counts of relevant keywords at time $t$, $G_t$, as a measure of the total number of people informed/concerned about the change in law in that time period. Then, the total number of people that have adapted to the change at time $t$, $T_G(t)$, is given by

$$TG_t(\rho) = G_t + \rho G_{t-1} + \rho^2 G_{t-2} + \cdots + \rho^T G_T.$$

Note that when we set the autocorrelation (i.e. memory) coefficient $\rho$ equal to 1 in this expression, we obtain nothing but $LC_t$, our proxy variable for the February 2012 change in check law. We want to find the value of $\rho$ for which the estimation of Equation (3) with $TG_t(\rho)$ replacing $LC_t$ provides the best fit (i.e. highest $R^2$). To this end, we grid search for $\rho$ in the interval $[0,1]$ with steps of 0.01 and estimate

$$y_t = \alpha + \gamma y_{t-1} + \beta X_t + \gamma TG_t(\rho) + \epsilon_t,$$

for each value of $\rho$, where everything is as defined before. This procedure yields a value of $\rho$ that is approximately equal to 0.96, implying that each month about 4 percent of people adapt to the change in the
check law. This, in turn, suggests that over 90 percent of people would adapt within 12 months following the change.\textsuperscript{20}

5. A model of decriminalization

In this section, we present a simple theoretical model that is consistent with our main empirical finding that the December 2011 break in the fraction of bad checks series can only be explained by the proxies for the February 2012 change in the check law that decriminalized bad check issuance.\textsuperscript{21} A key aspect of our model is that we suppose that the issuance of a check is equivalent to issuing debt. This assumption is motivated by the fact that checks are typically post-dated in Turkey, implying that checks are an instrument that facilitates borrowing and lending rather than merely a form of payment.

The model we consider is an investment game with a large population of entrepreneurs. Each entrepreneur observes a different investment opportunity and decides whether to undertake the investment or not. If the entrepreneur decides to invest, she issues a check to borrow the required amount of funds from lenders who are endowed with a large amount of loanable funds. If the investment is successful, the entrepreneur repays the lender and the game ends. If the investment is unsuccessful, some entrepreneurs fail to repay their debt to lenders. This is where the February 2012 amendments to the check law come into the picture. Prior to the change in law, entrepreneurs failing to honor their debt were sent to prison. Following the change in law, prison sentence was replaced with moderate monetary and administrative fines, leading to a substantial reduction in the severity of penalties. Accordingly, we model full decriminalization as leading to a reduction in the cost of issuing a bad check. Therefore, all else equal, a reduction in the cost of issuing a bad check induces a greater share of entrepreneurs to undertake investment opportunities that eventually fail, resulting in a rise in the incidence of bad checks.

Formally, we consider a large population where all entrepreneurs are identical in their net worths, $w > 0$, but differ in the investment opportunity, $(I_w, r_w, p_w)$, they face, where $I_w > 0$ is the amount of funds required to make the investment, $r_w > 0$ is the expected return on a successful investment (whereas an unsuccessful investment yields 0), and $p_w$ is the probability with which the investment succeeds. We assume that $p_w$ is distributed according to a continuous cumulative distribution function $F(p_w)$ over $(0,1)$ with $F(0) = 0$ and $F(1) = 1$, $I_w$ is distributed according to a continuous cumulative distribution function $G(I_w)$ over $(0,K)$ with $G(0) = 0$ and $G(K) = 1$ for some $K > w$, and $r_w = r > 0$. If an entrepreneur decides to undertake the investment opportunity, she uses her net worth $w$ as collateral and issues a check to borrow $I_w$ at interest rate $i$ from lenders with an infinitely elastic supply of capital. For

\textsuperscript{20} Repeating this analysis using web link counts from Google search engine provides similar results, indicating that our results are robust.

\textsuperscript{21} Recall that, in our empirical analyses, the breaks that occur in August 2008, March 2010, and May 2013 can all be fully accounted for by the proxies representing the state of the economic environment. The distinguishing feature of the December 2011 break is that the movements in the economic environment are insufficient in explaining it, unless the February 2012 legal change is also controlled for. Accordingly, our model is constructed so as to facilitate thinking about the interesting case of the December 2011 break; explaining all four structural breaks simultaneously would require a substantially richer model.
simplicity, we set \( i = 0 \). If an entrepreneur chooses not to invest, on the other hand, she receives 0. We also suppose that each entrepreneur has the same linear utility function \( u(x) = x \). Finally, we let \( c > 0 \) denote the proportional monetary cost imposed upon an entrepreneur defaulting on her debt at the time of repayment. To make the model interesting, we assume parameter values such that it is always optimal for at least some entrepreneurs to make investments.

Given this setup, the entrepreneurs’ decision problems can be analyzed in two parts: The decision problems of entrepreneurs with \( w \geq I_w \) and those with \( w < I_w \). The first case is rather uninteresting since an entrepreneur with \( w \geq I_w \) has a high enough collateral and never defaults on her debt, even when the investment fails. She invests as long as

\[
p_w \left( (1 + r)I_w - I_w \right) + (1 - p_w)(0 - I_w) \geq 0,
\]

which after rearrangement yields

\[
p_w \geq \frac{1}{1 + r} \equiv p_w^1.
\]

In other words, an entrepreneur with \( w \geq I_w \) invests only when the investment opportunity is sufficiently likely to be successful (i.e. when \( p_w \geq p_w^1 \)) and does not otherwise (i.e. when \( p_w < p_w^1 \)). Note also that a higher return on investment, \( r \), is associated with a lower \( p_w^1 \), thereby enlarging the set of success probabilities over which investments are undertaken.

In the second case where \( w < I_w \), by contrast, an entrepreneur’s collateral, \( w \), is not sufficient to cover her debt, \( I_w \), when the investment fails. The entrepreneur then ends up in default and a cost of \( c \) is imposed upon her. Accordingly, an entrepreneur with \( w < I_w \) will invest if and only if

\[
p_w \left( (1 + r)I_w - I_w \right) + (1 - p_w)(0 - (1 + c)I_w) \geq 0,
\]

or, equivalently,

\[
p_w \geq \frac{1 + c}{1 + r + c} \equiv p_w^{1+}.\]

Note that since \( p_w^{1+} > p_w^1 \), entrepreneurs with \( w < I_w \) have a higher minimum success probability threshold than entrepreneurs with \( w \geq I_w \) when deciding between investing or not. Moreover, \( p_w^{1+} \) increases with \( c \), implying that only those investment projects with sufficiently high success probability are actually implemented when the cost of falling in default is high.

In the equilibrium of this game, the number of defaults is given by,

\[
D = (1 - \alpha) \int_{p_w^1}^{1} (1 - p_w) dF(p_w),
\]

(A)

---

22 This assumption is also consistent with the fact that checks are not an interest-bearing instrument, at least explicitly.

23 \( p_w^{1+} - p_w^1 = \frac{1 + c}{1 + c + r} - \frac{1}{1 + r} = \frac{rc}{1 + c + r} > 0 \) since \( c > 0 \) and \( r > 0 \).

24 \( \frac{dp_w^{1+}}{dc} = \frac{1 + c - r - (1 - c)}{(1 + c + r)^2} = \frac{r}{(1 + c + r)^2} > 0 \) since \( r > 0 \).
where \( D \) denotes the equilibrium number of defaults and \( \alpha \in (0,1) \) denotes the fraction of entrepreneurs with \( w \geq l_w \). Equation A reflects the fact that defaults occur only for entrepreneurs with \( w < l_w \) (and hence for \( 1 - \alpha \) fraction of entrepreneurs) who decide to invest (those with \( p_w \geq p_\infty^* \equiv \frac{1+c}{1+c+\rho} \)) but whose investments fail (which happens with probability \( 1 - p_w \)). Note that since \( p_w \in (0,1) \), we have \( 1 - p_w > 0 \) and hence \( D > 0 \).

It is now straightforward to analyze the effect of a change that reduces \( c \), the entrepreneur’s cost of defaulting on debt, on the number of defaults, \( D \). Since \( p_\infty^* \) is increasing in \( c \), a fall in \( c \) reduces \( p_\infty^* \) and this, in turn, reduces the lower limit of the integral in Equation A. Because the integrand, \( 1 - p_w \), is non-negative for all \( p_w \in (0,1) \), the value of the integral in Equation A must go up. That is, a fall in the cost of defaulting on debt increases the number of defaults in equilibrium.\(^{25}\)

Intuitively, a fall in the cost of defaulting on debt (i.e. issuing a bad check) induces entrepreneurs to undertake investment projects with lower success probabilities, which then results in a higher number of defaults in equilibrium. Viewing the cost of issuing a bad check as a policy instrument chosen by lawmakers (imprisonment versus monetary and administrative fines), this result is nothing but a restatement of general deterrence according to which a marginal increase (decline) in expected punishment reduces (increases) the propensity to commit offenses, ceteris paribus. Note also that the cost of issuing a bad check has no bearing on the size of the investments undertaken by the entrepreneurs, as observed in the data. This latter implication holds as long as the size and the success probability of the investment are independently distributed, as we have assumed in the model.

6. Concluding remarks

In this paper, we present a test of general deterrence by means of exploiting a natural experiment produced by a shift in the law governing the usage of checks in Turkey. In particular, we show that the reductions in the severity of penalties for bad check issuance brought about by the February 2012 amendments led to a surge in the incidence of bad checks. Our finding, thus, corroborates the theory of general deterrence in the context of a developing economy.

We also find that economic agents were fairly quick to adapt to this change, which helped reduce the frequency of bad checks back to pre-legal change levels within twelve months. On the one hand, induced partly by the rules and regulations brought about by the February 2012 legal change, commercial banks have increased their screening efforts and raised their standards for opening check accounts and issuing checkbooks to clients. On the other, check holders appear to have become more restrained in accepting

\(^{25}\) More formally, suppose that \( c \) falls from \( c_1 \) to \( c_2 \) and as a result \( p_\infty^* \) falls from \( p_{1w} \) to \( p_{2w} \). Then, we must show \( D_2 = (1 - \alpha) \int_{p_{1w}}^{p_{2w}} (1 - p_w) dF(p_w) \) is greater than \( D_1 = (1 - \alpha) \int_{p_{1w}}^{p_{2w}} (1 - p_w) dF(p_w) \). Note that we can write \( D_2 = (1 - \alpha) \int_{p_{1w}}^{p_{2w}} (1 - p_w) dF(p_w) + (1 - \alpha) \int_{p_{1w}}^{p_{2w}} (1 - p_w) dF(p_w) = (1 - \alpha) \int_{p_{1w}}^{p_{2w}} (1 - p_w) dF(p_w) + D_1 \). Then, since \( p_{1w} > p_{2w} \) and \( p_w \in (0,1) \), we have \( \int_{p_{2w}}^{p_{1w}} (1 - p_w) dF(p_w) > 0 \) and hence \( D_2 > D_1 \).
checks, as indicated by the fall in the number of checks in circulation. The behavioral changes on the part of banks and check holders, thus, appear to have driven many of the check issuers who have failed or are likely to fail to honor their payments out of the market. The resultant improvement in the pool of check issuers, in turn, has led to a quite rapid adjustment in the incidence of bad checks. Meanwhile, the increased efforts of quasi-governmental institutions such as the Credit Registration Bureau and the Banks Association of Turkey Risk Center in disseminating detailed information on the past payment behavior of check issuers appear to have strengthened the ability of both banks’ and check holders’ to screen out unworthy borrowers. In fact, we conjecture that had these two institutions entered the game in early 2011 rather than in 2012-13, the observed surge in bad checks due the change in the check law would have been considerably smaller in magnitude and lasted for much shorter.

These findings suggest that sanctions need not be draconian to deter wrongful behavior as long as appropriate infrastructures that will enable efficient behavioral adjustments are instituted in a timely manner. This conclusion is consistent with the notion that imprisonment should be the sanction of last resort since it hurts the criminal but (excluding sentiments of revenge and hatred) it does not promote, unlike monetary sanctions, the well-being of the victim and it also imposes great costs on society (see, for example, Harel, 2012; Fisher, 2014). In principle, imprisonment may be preferred over monetary sanctions when one or more of the following conditions materialize. First, the offender is insolvent (relative to the harm he has caused), which makes it impossible to compensate the victim. Second, the benefits of incapacitation are very large. Third, the harm is inflicted on multiple victims each of whom individually has very little incentive to seek legal remedy. Fourth, the probability of detection is low. However, none of these conditions seems to loom large in the context of bad check issuance, at least in today’s Turkey. Therefore, despite our reservations about the handling of the transition, we believe that the decriminalization of bad check issuance in Turkey has been a step in the right direction.26

References


26 Referring to Schäfer (2013) and Cooter and Schäfer (2012), Babaoglu and Wulf (2015) argue that countries should shift from criminal sanctions to civil sanctions as their economies develop and their citizens get wealthier, and that these theoretical considerations might also justify the February 2012 policy shift in Turkey. We concur with this view.


<table>
<thead>
<tr>
<th>Fraction of Bad Check Counts (First Lag)</th>
<th>Fraction of Bad Check Counts</th>
<th>Fraction of Bad Check Counts</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.400</td>
<td>0.410</td>
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</tbody>
</table>

**Table 1 - Regression Results**

(Dependent Variable: Fraction of Bad Check Counts)
<table>
<thead>
<tr>
<th>Indicator</th>
<th>Coefficient 1</th>
<th>Coefficient 2</th>
<th>p-value 1</th>
<th>p-value 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Legal Change Proxy 1 (Based on Google Trends)</td>
<td>0.000582</td>
<td>—</td>
<td>(5.00)***</td>
<td>(5.20)***</td>
</tr>
<tr>
<td>Legal Change Proxy 2 (Based on Google Search)</td>
<td>—</td>
<td>0.000174</td>
<td>(4.76)***</td>
<td>(4.57)***</td>
</tr>
<tr>
<td>Industrial Production Index</td>
<td>-0.0185</td>
<td>-0.0150</td>
<td>(-2.41)**</td>
<td>(-1.89)*</td>
</tr>
<tr>
<td>Borsa Istanbul 100 Index</td>
<td>-0.0000302</td>
<td>-0.000282</td>
<td>(-4.79)***</td>
<td>(-4.61)***</td>
</tr>
<tr>
<td>Real Sector Confidence Index</td>
<td>-0.00649</td>
<td>-0.00993</td>
<td>(-0.86)</td>
<td>(-1.29)</td>
</tr>
<tr>
<td>Number of Protested Bills</td>
<td>0.0000186</td>
<td>0.0000164</td>
<td>(4.54)***</td>
<td>(4.18)***</td>
</tr>
<tr>
<td>Non-Performing Loans Ratio</td>
<td>0.261</td>
<td>0.265</td>
<td>(2.88)***</td>
<td>(2.83)***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Observations</th>
<th>123</th>
<th>123</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.886</td>
<td>0.885</td>
</tr>
</tbody>
</table>

*p-values are shown with stars (* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$)

![Figure 1. Fraction of bad check counts (The ratio of the number of bad checks to the number of all checks)](image-url)
Figure 2. Fraction of bad check values (The ratio of the value of bad checks to the value of all checks)
Figure 3. Total number of checks compared
Figure 4. Fraction of bad check counts compared
Figure 5. Structural breaks in the fraction of bad check counts
Figure 6: Break statistics for the fraction of bad check counts after controlling for the state of the economic environment
Figure 7. Search counts from Google Trend
Figure 8: Break statistics for the fraction of bad check counts after controlling for both the state of the economic environment and the Google trend proxy for the February 2012 change in check law.
Figure 9. Search query counts from Google Search Engine
Figure 10: Break statistics for the fraction of bad check counts after controlling for both the state of the economic environment and the Google search engine proxy for the February 2012 change in check law.
Figure 11: Break statistics for the (detrended) average bad check value after controlling for the state of the economic environment

Max QLR = 11.26, at 2013m6

Critical value 5% (8.68)