Labor Market Concentration, Minimum Wages, and Local Property Crime Rates*

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This paper investigates how labor market concentration moderates the effect of the minimum wage on crime. The rationale for this comes from economic theory: a Becker-Ehrlich model suggests that crime is negatively related to wages and employment, and classical monopsony theory suggests that the minimum wage can increase wages and employment when labor markets are concentrated. I use administrative data from the FBI to measure local property crime rates and firm-level data from Lightcast to measure local labor market concentration. Consistent with the theory, I find that a 1% increase in the minimum wage is associated with a 0.37% increase in employment and a 0.56% decrease in larceny-theft in the most concentrated markets. My results suggest that the degree of imperfect competition in the local labor market has important implications for the spillover effects of the minimum wage on local property crime rates.

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1. Introduction

Crime in the U.S. poses a significant burden, with estimated annual costs between \$4.71-\$5.76 trillion dollars (Anderson, 2021). In 2016, the Council of Economic Advisors (CEA) advocated for using the minimum wage to reduce crime, arguing that an effective way to reduce crime is to increase economic opportunity (CEA, 2016). This paper investigates whether the minimum wage can be used to reduce property crime, and whether the effect of the minimum wage on crime depends on the local labor market structure.

Theory suggests that the minimum wage has two effects on crime: a "wage effect" and an "employment effect". In a Becker-Ehrlich model, the legal wage is the opportunity cost of crime, and therefore higher wages should discourage individuals from criminal behavior (the "wage effect"). On the other hand, in a perfectly competitive labor market, the the minimum wage reduces employment, and the Becker-Ehrlich model predicts that job loss increases an individual's propensity for criminal behavior (the "employment effect"). Thus, when labor markets are perfectly competitive, the net effect of the minimum wage on crime depends on whether the wage effect or the employment effect dominates.

However, the theoretical prediction is different if local labor markets are imperfectly competitive. When labor markets are characterized by imperfect competition, firms mark down wages below marginal revenue product, and therefore firms can accommodate higher wages without laying off workers. Recent empirical work has documented a positive effect of the minimum wage in highly concentrated markets, consistent with a Cournot model of oligopsony (Azar, Huet-Vaughn, Marinescu, Taska, & Von Wachter, 2019). Since the minimum wage increases both employment and wages in highly concentrated markets, and the Becker-Ehrlich model suggests that wages and employment are negatively related to crime, it follows that the minimum wage should decrease property crime when markets are concentrated.

I outline a simple theoretical framework that formalizes the intuition described above. My model makes sharp predictions about the effect of the minimum wage on crime: in the model, the effect of a small increase in the minimum wage on crime is unambiguously negative when firms compete for labor à la Cournot. This is in contrast to the prediction of the model if labor markets are perfectly competitive: under perfect competition, the net effect of the minimum wage on crime is ambiguous due to the opposing wage and employment effects. In addition, the theoretical framework predicts that the magnitude of the crime elasticity of the minimum wage should increase when labor market concentration increases, since labor market concentration is positively correlated to the wage markdown when firms compete à la Cournot.

The data used in the empirical analysis come from a variety of sources. Data on crime comes from the FBI's Uniform Crime Reporting (UCR) program (Kaplan, 2019a). I focus on larceny-theft as my main outcome variable since this is the type of property crime recorded in the UCR that is most likely to be related to changes in the minimum wage. I also report results for two other property crimes that are available in the UCR: burglary and motor-vehicle theft. The firm-level data used to calculate labor market concentration comes from Lightcast. Other data sources include the Quarterly Census of Employment and Wages (QCEW) and Local Area Unemployment Statistics (LAUS).

Empirically, my empirical strategy is similar to Azar, Huet-Vaughn, et al. (2019). The "first stage" of my analysis seeks to replicate Azar, Huet-Vaughn, et al. (2019) by estimating a two-way fixed effects model of the effect of the minimum wage on employment. In the "second stage", I deviate from Azar, Huet-Vaughn, et al. (2019) by using a similar two-way fixed effects model to investigate the effect of the minimum wage on local property crime rates. These "second stage" results are novel – to the best of my knowledge, no previous studies have investigated how local labor market concentration moderates the effect of the minimum wage on crime. Note that in my "second-stage" regressions, I augment the baseline specification in Azar, Huet-Vaughn, et al. (2019) by including several important control variables – clearance rates, violent crime, and the total number of agencies reporting. Violent crime proxies for unobserved changes in local crime trends, and clearance rates proxy for changes in local law-enforcement practices (Braun, 2019). These control variables are important because crime is highly dependent on policy, and criminal justice policy may be correlated with minimum wage legislation.

My empirical estimates are consistent with the hypotheses generated by the theory. In the most concentrated markets (defined as markets with concentration above 0.25), I find that a 1% increase in the minimum wage is associated with a 0.25 to 0.52% increase in employment and a 0.53 to 0.60% decrease in larceny-theft. If I assume that the mechanism driving the effect of the minimum wage on crime is entirely an employment effect, for the average county we see a decrease in 0.81 larceny-theft incidents per every additional individual employed. I do not find any strong evidence that the minimum wage affects burglary or motor-vehicle theft.

I conduct "placebo regressions" whereby I estimate my main empirical specifications with violent crime as the dependent variable (excluding violent crime on the right-hand side). The point estimates from these placebo regressions are not statistically significant, and their signs are typically the opposite of the signs of the point estimates for the effects on property crime. This is reassuring and suggests that my main results for property crimes are not being driven by unobservable trends in crime or crime reporting.

My results are related to several strands of literature. The paper is most closely related to the existing studies that investigate the effect of the minimum wage on crime. These studies tend to produce conflicting results and no clear consensus is apparent: some authors find that the minimum wage increases crime (e.g. see Hashimoto (1987), Beauchamp and Chan (2014), Fone, Sabia, and Cesur (2019), Braun (2019)), while others have found that the minimum wage decreases crime (see Fernandez, Holman, and Pepper (2014) and Agan and Makowsky (2018)).[1] The estimates in these papers can be quite different: Fone et al. (2019) find that a 1% increase in the minimum wage increases arrests among 16 to 24 year olds by 0.2%, and Agan and Makowsky (2018) find that a minimum wage increase of $0.50 decreases the probability of returning to prison by 2.8%. My paper complements the existing studies on the minimum wage and crime by examining the moderating effect of imperfect competition in the legal labor market. To the best of my knowledge, no study on the effect of minimum wage in crime considers whether the crime-elasticity of the minimum wage depends on local labor market concentration.

The paper is also related to research on the relationship between crime, wages, and employment more generally that began with the seminal papers by Becker (1968) and Ehrlich (1973). Becker (1968) and Ehrlich (1973) conceptualize criminal behavior as a utility maximizing choice that depends on relative costs and benefits. There is a large literature testing reduced form relationships between employment or wages and local crime rates (e.g. Grogger (1998), Raphael and

[1] The conflicting results in the minimum-wage-on-crime literature parallel the conflicting results in the minimum-wage-on-employment literature. There is a long-standing debate in the minimum wage literature about whether or not the minimum wage causes disemployment (e.g., see Neumark and Wascher (1992); Card and Krueger (1994); Dube, Lester, and Reich (2010); Meer and West (2016); Jardim et al. (2017); Clemens and Wither (2019); Cengiz, Dube, Lindner, and Zipperer (2019); Harasztosi and Lindner (2019); Derenoncourt and Montialoux (2020); for a full review of the literature see Neumark et al. (2013) and Allegretto, Dube, Reich, and Zipperer (2017)). In a recent paper, Azar, Huet-Vaughn, et al. (2019) show that labor market concentration is a powerful moderator of the effect of the minimum wage on employment and that labor market concentration explains the diversity of effect sizes documented in the minimum-wage-on-employment literature. If labor market concentration moderates the effect of the minimum wage on employment, and if employment and wages are related to local crime rates, then labor market concentration should also moderate the effect of the minimum wage on crime.

Winter-Ebmer (2001), Gould, Weinberg, and Mustard (2002), Yang (2017); see Chalfin and McCrary (2017) for a full review)). Recent papers by Rose (2018) and Bennett and Ouazad (2020) use administrative microdata to investigate the causal effect of employment on crime: Bennett and Ouazad (2020) find that job displacement in a mass lay-off increases the likelihood of property offenses by 0.38 percentage points, and Rose (2018) finds a 30% increase in the likelihood of offending in the three years following job loss. My paper contributes to Becker-Ehrlich tradition by measuring the combined employment and wage effects of the minimum wage on property crime when labor markets are concentrated. Unfortunately, I cannot disentangle the "employment" and "wage" effects of the minimum wage since minimum wages increase both wages and employment simultaneously; however, further disentangling these two effects is scope for future research.

My paper is also indirectly related to the growing literature that documents pervasive monopsony power in U.S. labor markets (e.g. see Kroft, Luo, Mogstad, and Setzler (2020), Lamadon, Mogstad, and Setzler (2019), Qiu and Sojourner (2019), Berry, Gaynor, and Morton (2019), Arnold (2019), Schubert, Stansbury, and Taska (2020), and Azar, Marinescu, and Steinbaum (2019); see Manning (2020) for a review). Recent work by Azar, Marinescu, Steinbaum, and Taska (2020) has documented that over 60% of U.S. labor markets are highly concentrated, and related work by Azar, Huet-Vaughn, et al. (2019) has shown that labor market concentration moderates the effect of the minimum wage on employment. One of the main take-aways of my paper is that researchers should not ignore imperfect competition in the legal labor market, even when studying spill over effects of economic policies on non-economic outcome variables.

The rest of this paper is organized as follows. Section 2 explains the conceptual framework. Section 3 outlines the data used. Section 4 describes the empirical strategy. Section 5 explains the results. Finally, section 6 concludes.

2. Theory

In this section, I outline a simple model that highlights the theoretical relationship between local property crime rates, minimum wages, and local labor market concentration. The model combines insights from a Becker model of crime (Becker, 1968; Ehrlich, 1973; Grogger, 1998; Agan & Makowsky, 2018; Rose, 2018) with insights from an imperfectly competitive model of the low-wage legal labor market (Azar, Huet-Vaughn, et al., 2019; Boal & Ransom, 1997).

Assume there is a unit mass of workers who each decide how to allocate an hour of their time at time between property crime, legal work, or non-participation. Implicitly, I am assuming that worker's do not have specific preferences over their firm or occupation.[2] These implicit assumptions are appropriate because I focus on the trade-off between legal work and criminal behavior. Worker i in market m has the following utility functions associated with each choice at time t:

$$u^c_{imt} = \log(w^c_{mt}) + \varepsilon^c_{imt} \tag{1}$$

$$u^l_{imt} = \log(w^l_{mt}) + \varepsilon^l_{imt} \tag{2}$$

$$u^n_{imt} = \log(w^n_{mt}) + \varepsilon^n_{imt} \tag{3}$$

where equation (1) corresponds to the utility of property crime, equation (2) corresponds to the utility of legal work, and equation (3) corresponds to the utility of non-participation. The parameters w^c_{mt}, w^l_{mt}, and w^n_{mt} correspond to the returns (in dollars) of one hour of each respective activity, and the residuals $\varepsilon^c_{imt}, \varepsilon^l_{imt}$, and ε^n_{imt} are random variables that represent individual preference shocks. Allowing for heterogeneous preferences captures the notion that different individuals in society have different propensities to engage in illegal activity: $w^c_{mt} > w^l_{mt}$ is not a sufficient condition for an individual to engage in crime.

For simplicity I assume that the return to one hour of crime is constant and exogenously determined.[3] The return to work w^l_{mt} is the wage for one hour work in the low-wage labor market, and this parameter is affected if the government implements a binding minimum wage. The dollar return to non-participation is a dollar value associated with government benefits that non-employed individuals are eligible to receive.

In what follows, for tractability I assume that each individual i is located in only one market m and each individual i's preference shocks $\varepsilon^c_{imt}, \varepsilon^l_{imt}, \varepsilon^n_{imt}$ are mutually independent at time t and distributed according to an extreme value type 1 distribution. Given that there is a unit mass of consumers, the total supply of property crime at time t in market m is given by $Q^c_{mt}(w^c_{mt}|w^l_{mt}, w^n_{mt}) \equiv \mathbb{P}[u^c_{imt} \geq u^l_{imt}, u^c_{imt} \geq u^n_{imt}]$.

In each legal labor market m, assume that there are N_m identical firms. The assumption of identical firms is made for analytical convenience and is not necessary

[2] I do not include firm-specific amenities that generate monopsony models in many other of the models in the literature. Instead, monopsony power in my model is generated by strategic behavior by firms.

[3] In a more detailed model of criminal behavior, the 'demand' in the criminal market reflects society's tolerance for crime as well as criminal opportunities (Agan & Makowsky, 2018; Grogger, 1998).

to generate the hypotheses outlined below. Assume that each firm has production technology $f(q^l_{jmt})$, where q^l_{mjt} is the quantity of legal labor demanded by firm j in market m at time t. Assume that $f(.)$ is twice continuously differentiable with $f'(.) > 0$ and $f''(.) < 0$. Denote the total quantity of legal labor demanded in the market by $Q^l_{mt} = \sum_{j=1}^{N_m} q^l_{jmt}$.

The first proposition shows that we can decompose the effect of the minimum wage on crime into the sum of an "employment effect" and "wage effect" when labor markets are perfectly competitive:

Proposition 1. Assume that labor markets are characterized by perfect competition, so that firms are wage-takers in the legal labor market. Suppose that the government implements a minimum wage $\overline{w}^*$ that "just binds." Then we can decompose the effect of a small increase in the minimum wage on crime into the sum of an "employment effect" and "wage effect":

$$\begin{aligned}(4)\qquad &\frac{\partial Q^c_{mt}(w^c_{mt}|w^l_{mt} = \overline{w}^*, w^n_{mt})}{\partial \overline{w}^*} = \\ &\underbrace{-\frac{Q^c_{mt}}{w^c_{mt} + \overline{w}^* + w^n_{mt}}}_{\text{Wage effect (negative)}} + \underbrace{\left(\frac{Q^c_{mt} + Q^n_{mt}}{w^c_{mt} + \overline{w}^* + w^n_{mt}} - \frac{dF'^{-1}(\overline{w}^*)}{dw^l_{mt}}\right)\frac{w^c_{mt}}{w^c_{mt} + w^n_{mt}}}_{\text{Employment effect (positive)}}\end{aligned}$$

Proposition 1 shows that the total effect of the minimum wage on crime in a perfectly competitive market is ambiguous according to theory. This ambiguity results because of two opposing effects: on the one hand, a higher wage increases the opportunity cost of crime and thus decreases the number of consumers who are willing to spend an hour engaged in property crime. On the other hand, wage-taking in the legal labor market implies that the minimum wage has disemployment effects, and individuals who are displaced from legal work due to the minimum wage may turn to property crime as a source of income.

However, the ambiguous effect of the minimum wage on crime disappears if we assume that firms have wage-setting power. The next proposition shows that the effect of the minimum wage on crime is unambiguously negative if firms compete for legal labor a la Cournot:

Proposition 2. Assume that labor markets are characterized by Cournot competition, so that firms are competing in quantities in the legal labor market. Suppose that the government implements a minimum wage $\overline{w}^*_{cournot}$ that "just binds." Then we the effect of a small increase in the minimum wage on crime is unambiguously negative:

$$\frac{\partial Q^c_{mt}(w^c_{mt}|w^l_{mt} = \overline{w}^*_{cournot}, w^n_{mt})}{\partial \overline{w}^*_{cournot'}} = -\underbrace{\frac{Q^c_{mt}}{w^c_{mt} + \overline{w}^*_{cournot} + w_n}}_{\text{Wage effect (negative)}}. \tag{5}$$

Intuitively, when firms are wage-setting in the legal labor market, wages are marked down below marginal revenue product and so firms can accommodate higher wages without lay-offs. Thus in Proposition 2 there is no "employment effect": workers earn a higher wage from legal work and all individuals who choose to work in the legal labor market are able to do so. Employment *rises* in the legal labor market as a result of the minimum wage increase, and property crime falls.

In addition, as long as we are willing to assume diminishing marginal utility over wages,[4] we can show that the magnitude of the effect of the minimum wage on crime is an increasing function of local labor market concentration when labor markets are imperfectly competitive. This relationship occurs because wage mark downs are higher in labor markets that are more concentrated. The next proposition shows this formally:

Proposition 3. Assume that labor markets are characterized by Cournot competition, so that firms are competing in quantities in the legal labor market. Suppose that the government implements a minimum wage $\overline{w}^*_{cournot}$ that "just binds." Then the effect of the minimum wage on crime is negative and the magnitude is an increasing function of local labor market concentration:

$$\frac{\partial^2 Q^c_{mt}}{\partial N_m^{-1} \partial \overline{w}^*_{cournot}} =$$
$$\frac{2Q^c_{mt}(w^n_{mt} + w^c_{mt})}{(1 - Q^l_{mt})^2} \left[\frac{f''(Q^l_{mt}/N_m) - (W^l_{mt})' Q^l_{mt}}{-f''(Q^l_{mt}/N_m) + (W^l_{mt})'' Q^l_{mt}/N_m + (W^l_{mt})'/N_m + (W^l_{mt})''} \right] < 0,$$

where W^l_{mt} is the inverse legal labor supply function in market m at time t so that $(W^l_{mt})' = \frac{w^n_{mt}+w^c_{mt}}{(1-Q^l_{mt})^2} > 0$ and $(W^l_{mt})'' = \frac{2(w^n_{mt}+w^c_{mt})}{(1-Q^l_{mt})^3} > 0$.

The theory outlined above lays the foundation for the empirical analysis of this paper and suggests the following two hypotheses:

Hypothesis 1. The crime elasticity of the minimum wage is negative in concentrated labor markets (see proposition 2)

[4] This assumption is captured in the current model when we assume that the worker's utility is a function of the natural logarithm of the hourly wage in crime, legal work, or non-participation. Another concave function other than the natural logarithm would also be sufficient to generate the hypotheses.

Hypothesis 2. The magnitude of the crime elasticity of the minimum wage will be larger when labor market concentration is higher (see proposition 3)

3. Data

3.A. Crime data

Crime data come from FBI's Uniform Crime Reporting (UCR) Program, compiled by Jacob Kaplan and available through the Interuniversity Consortium of Political and Social Research (ICPSR) website (Kaplan, 2019a). The UCR data is the most comprehensive publicly available data on crime in the United States, obtained from over 18,000 participating law-enforcement agencies that report crime-related information on a monthly basis (Kaplan, 2023). Notable papers in the economics literature that use the UCR data include Mas (2006), Chalfin (2014), Bove and Gavrilova (2017), and Braun (2019).[5]

The main crime variables used in my analyses are larceny-theft, burglary, and motor-vehicle theft. Theft is divided into two subcategories in the UCR: larceny-theft and motor-vehicle theft. Larceny-theft is defined as "the unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another" (U.S. Department of Justice, 2013).[6] Examples of offenses categorized as larceny-theft include pocket-picking, purse-snatching, shoplifting, theft of bicycles, theft from buildings, etc. I focus on these crimes in particular because these are the property crimes for which data exists in the UCR.[7]

Participation in the UCR program is voluntary, and not all police agencies participate in the UCR program. To control for changes in policy agency participation, in my preferred specifications I directly control for the number of police agencies reporting, violent crimes, and arson. I include controls for violent crimes and arson because changes in the minimum wage should not affect these crimes, and therefore these controls account for changes in agency reporting, general changes in law enforcement practices, and county-level crime trends (Braun, 2019).

[5]Kaplan (2023) explains that as of 2021, a google scholar search of "county-level UCR" returns 3,780 results.

[6]Constructive possession is defined as "control or dominion over a property without actual possession or custody of it" (U.S. Department of Justice, 2013).

[7]Note that the UCR reporting follows the 'hierarchy rule': when several crimes committed by the same perpetrator(s) are reported to the law-enforcement agency, only the most serious crime is recorded in the dataset (U.S. Department of Justice, 2013). The hierarchy, from most serious to least serious, is homicide, rape, robbery, aggravated assault, burglary, theft (other than of a motor vehicle), motor vehicle theft, arson, simple assault (Kaplan, 2023). If an individual commits larceny-theft and murder, for example, only murder will be recorded in the data.

In addition, a known problem with the UCR data is that if law-enforcement agency is recorded as having a value of “0” for a crime in a particular month, this could indicate that there were no crimes in that month, but it could also indicate that the law-enforcement agency chose not to report their crimes to the UCR program in that month (see Kaplan (2023)). Therefore, before aggregating the agency-month level UCR data to the county-year-quarter level, I restrict the sample to agencies that report at least one crime (either larceny-theft, burglary, motor-vehicle theft, arson, or any violent crime) for all 12 months of every year that they appear in the data.[8,9] Since my identification strategy relies on the relationship between *changes* in minimum wages and *changes* in local property crime rates (conditional on controls), restricting the sample to law-enforcement agencies that consistently report crimes each month is unlikely to bias the estimates.

Finally, it is important to acknowledge that not all crimes are reported to law enforcement. For example, only one-third of larceny-theft crimes are reported to police agencies (Raphael, 2016). Therefore, the crime rates in the UCR are likely lower bounds of true crime rates. As mentioned above, my empirical specification investigates the relationship between changes in the minimum wage and changes in larceny-theft rates, and therefore under-reporting of crimes to law enforcement is unlikely to bias the results unless changes in reporting are systematically correlated with changes in the minimum wage (conditional on controls).

3.B. Lightcast Vacancy Data

The firm-level dataset on job vacancies comes from Lightcase. The Lightcast data contains the near universe of online US job vacancies from about 50,000 websites. It includes detailed information on each job vacancy, such as the occupation, location, and employer name. It also contains information on the task content and education requirements of job postings. Most importantly, the Lightcast dataset contains detailed firm-level information on vacancies that can be used to construct local measures of employer concentration.

Not all occupations are equally well-represented in the Lightcast data (Hershbein & Kahn, 2018; Azar, Huet-Vaughn, et al., 2019). Due to data limitations in the

[8] After applying this filter to the data, 0.7% of remaining UCR sample (distributed across 3.9% of the remaining agencies) have a value of “0” recorded for a month in year where the average number of crimes per month is at least 10 for one of larceny-theft, motor-vehicle-theft, or burglary. It is possible that these are data errors or non-reports of law-enforcement agencies masquerading as “0”’s. The results are virtually identical if I remove these agencies.

[9] I also drop 2 agencies due to clear data entry errors: “GA10800” (an agency in Oconee County, Georgia) and “AL00201” (an agency in Mobile County, Alabama). The results do not change if these agencies are included.

Lightcast data, I am only able to credibly measure labor market concentration for three occupations that typically pay the minimum wage: Cashiers (SOC 412011), Retail Salespersons (SOC 412031), and Stock Clerks (SOC 435081). Note that these are the exact same retail occupations studied in Azar, Huet-Vaughn, et al. (2019), and the reader is referred to their paper for a discussion about why these are the only minimum-wage occupations for which labor market concentration can be credibly estimated in the Lightcast data.

Following Azar, Huet-Vaughn, et al. (2019), for each county r, and for each occupation $o \in \{412011, 412031, 435081\}$, I calculate the Herfindahl–Hirschman Index (HHI) at time t as:

$$HHI_{ort} = \sum_{j=1}^{N_{rt}} \left(\frac{q_{jort}}{\sum_{j=1}^{N_{rt}} q_{jort}} \right)^2, \tag{6}$$

where q_{jort} is employer j's number of vacancy postings for occupation o in market m at time t, and N_{rt} is the number of firms in county r at time t. Note that I identify different employers using the employer *name* associated with each vacancy posting (following Schubert et al. (2020), Azar et al. (2020), and Azar, Huet-Vaughn, et al. (2019)). For vacancies that are missing the employer name, I assume that each vacancy corresponds to a different employer. This approach to calculating HHI is conservative and will tend to understate the degree of employer concentration for two reasons. First, it is possible that two vacancies with different employer names correspond to the same employer, for example if two firms are owned by the same individual corporation. Second, it is possible that vacancies that are missing employer names have been posted by other firms in the database.

Following Azar, Huet-Vaughn, et al. (2019), the main measure of labor market concentration for occupational market o in county r is calculated as the average HHI_{ort} over all time periods in the data:

$$\overline{HHI}_{or} \equiv \frac{1}{28} \sum_{t} HHI_{ort}. \tag{7}$$

Azar, Huet-Vaughn, et al. (2019) explain that this measure more accurately captures underlying labor market concentration compared to a time varying measure because variation in vacancies may result from changes in economic conditions. In my robustness checks, I re-run all of my main results using a pre-determined HHI measure, and the results are similar.

A possible concern is that I am calculating local concentration using *vacancies* (which are closely related to employment flows) instead of *employment stocks* at each firm. In equilibrium, measures of concentration using vacancies or employment stocks should be highly correlated, although vacancies should respond more to local market conditions in the short run. Reassuringly, Marinescu, Ouss, and Pape (2019) find that HHI calculated using employment flows (which are similar to vacancies) is highly positively correlated with HHI calculated using employment stocks in French administrative data, suggesting that my results would be similar if I used a concentration measure calculated with employment stocks.

It is also worth noting that my estimate of labor market concentration using the Lightcast data may understate true concentration if larger firms tend to hire more than one worker for each job posting. In that case, measures of concentration calculated using the Lightcast data will tend to understate true employer concentration; see Schubert et al. (2020) for more details.

3.C. Other data

Other variables used in my analyses come from a variety of sources. Data on county-level unemployment rates and total employment come from the BLS Local Area Unemployment Statistics (LAUS), and data on total earnings or employment for the retail industry come from the Quarterly Census of Employment and Wages (QCEW). County-level population data come from the Survey of Epidemiology and End Results (SEER), available publicly through the National Bureau of Economic Research (NBER). Summary statistics for the data are presented in Table 1. In addition, Table A1 in the appendix summarizes the data used in this paper and the sources.

The final dataset has a sample period of 2010 to 2016 with time variation at the quarterly level. Figure 1 shows the variation of the minimum wage across U.S. states and over time during this period.

4. Empirical Strategy

My empirical strategy is similar to the one used in Azar, Huet-Vaughn, et al. (2019), although I augment the baseline empirical specification in Azar, Huet-Vaughn, et al. (2019) by adding additional control variables that are important in my context. Azar, Huet-Vaughn, et al. (2019) focus on the retail sector and they show that the employment elasticity of the minimum wage in the retail industry (NAICS 452) is a positive function of the Hirschman Herfindahl Index (HHI) of three retail occupations: stock clerks and order fillers (SOC 43-5081), retail sales (SOC 41-2031) and cashiers (SOC 41-2011). I first attempt to replicate the results in Azar, Huet-Vaughn, et al. (2019) by measuring how the effect of the minimum wage on employment varies by labor market concentration for these same three occupational labor markets. This is the “first stage” of my analysis. To do this, I use the exact same specification as the main specification in Azar, Huet-Vaughn, et al. (2019). The “second stage” of my analysis studies how labor market concentration in the occupational labor markets for stock clerks, retail sales, and cashiers. These “second-stage” results are novel and the main contribution of this paper, so I focus on the empirical strategy used for the “second stage” in my discussion below.

Before describing the main empirical specification, I note that one of the main motivations for investigating the effect of the minimum wage on crime is the empirical finding that younger adults are disproportionately likely to work minimum wage jobs and engage in property crimes compared to other age demographics (Braun, 2019; Fone et al., 2019). Figure A1 in the Appendix shows that the majority of individuals arrested for larceny-theft tend to be young adults and that young adults also make up the the majority of those working as sales counter clerks or cashiers.

The main empirical specification is:

$$\log(Y_{rt}) = \alpha + \beta \log(MW_{rt}) + \delta \log(MW_{rt}) \times \overline{HHI}_{or} + \gamma X_{rt} + \eta_r + \tau_{ct} + \chi I_s + \varepsilon_{rt} \tag{8}$$

where Y_{rt} is the outcome variable (e.g. crime rate, employment, etc.) for county r in quarter t, MW_{rt} is the minimum wage (the maximum between the federal or state), $\overline{HHI}_{or}$ is the average HHI for a retail occupation o for county r, η_r are commuting zone fixed effects, τ_{ct} are census-region-specific year-quarter fixed effects, χI_s are state-specific linear time trends, and X_{rt} is a vector of controls.[10] In the baseline specification, the vector of controls X_{rt} includes the log of population, the log of the unemployment rate, the log of total employment (for all industries), and the log of total earnings (Azar, Huet-Vaughn, et al. (2019)). In the preferred specification, I also include variables that control for trends in crime and unobserved changes in police practices: clearance rates for property and violent crimes, the log of violent crimes, and the number of police agencies reporting. Later in this section, I discuss the rationale for each of the control variables included. A

[10] I only include the interaction term of the concentration index with the minimum wage (and not the concentration index itself) in the main empirical specification because the concentration index does not vary over time. This implies that the coefficient of the concentration index by itself is not identified when CZ-level fixed effects are included.

summary of the control variables is also included in the Appendix Table A1, with summary statistics in Table 1. Standard errors are clustered at the state level.

I estimate an additional specification that includes a dummy variable that indicates whether the local labor market is "highly concentrated":

$$\log(Y_{rt}) = \alpha + \beta \log(MW_{rt}) + \delta \log(MW_{rt}) \times \mathbb{1}[\overline{HHI}_{or} \geq 0.25] + \gamma X_{rt} + \eta_r + \tau_{ct} + \chi I_s + \varepsilon_{rt}, \tag{9}$$

where the value of "0.25" is chosen to define highly concentrated labor markets, and the other terms are defined in the same way as in equation 8. The rationale for using "0.25" as the cut-off for the definition of "highly concentrated" is that this is the threshold used by the U.S. Department of Justice (DOJ) in analyses of horizontal mergers and acquisitions.

In the vector of controls, I include all of the variables that are in the main specification of Azar, Huet-Vaughn, et al. (2019): the log of total population, the log of total employment, the log of total earnings, and the log of the unemployment rate. These controls are included for the following reasons. First, concentration is correlated with population and productivity (and total earnings is a proxy for total productivity in the region). Second, total employment and the unemployment rate proxy for changes in economic conditions, and it is likely that economic conditions are correlated with changes in the minimum wage.

I also include several crime control variables that are important because measured crime statistics are highly dependent on criminal-justice policy. I follow Braun (2019) by including the log of clearance rates (for property and violent crimes) and the log of violent crime.[11] In addition, I also include the total number of agencies reporting. Clearance rates proxy for unobserved changes in law enforcement practices, and the total number of agencies reporting and the log of violent crime proxy for changes in underlying crime trends or crime reporting (Braun, 2019).

In my robustness checks, I include the fraction of individuals in various age, sex, and race categories to control for changes in demographic variables over time. Specifically, I include the fraction within the following age categories: 16-24, 25-34, 35-44, 45-54, 55-64, and 65+.I also include the fraction white and the fraction male.

[11] An offense is 'cleared by arrest' when the perpetrators are caught and arrested. Clearance rates are therefore defined as the number of individuals arrested for crimes divided by the number of crimes reported.

5. Results

The main results for employment in the specification without crime controls are presented in Tables 2 and 3 (without crime controls) and tables 10 and 11 (with crime controls). The results without crime controls in Tables 2 and 3 mirror Azar, Huet-Vaughn, et al. (2019), but my preferred specification includes the crime controls in Tables 10 and 11. Table 10 shows that there is a highly significant positive association between average HHI and the employment elasticity of the minimum wage. In Table 11, we see that, in the counties that are highly concentrated, a 1% increase in the minimum wage increases employment by 0.248% (Stock Clerks), 0.518% (Retail Sales), and 0.293% (Cashiers). The average of these three point estimates is 0.371%, which suggests that, for the average county in the data, a 1% increase in the minimum wage increases employment by about 0.37%.[12] This implies that, for the average county in the data, a 10 cent increase in the minimum wage is associated with an increase in 5.5 workers.

The main results for crime rates are presented in Tables 12 to 17 (with crime controls). Tables 4 to 9 contain results without crime controls. In Table 12 we see that the larceny-theft elasticity of the minimum wage is negatively associated with labor market concentration for all three occupational labor markets, consistent with hypothesis 3. Table 13 shows that a 1% increase in the minimum wage lowers larceny theft by 0.530% (Stock Clerks), 0.603% (Retail Sales), and 0.558% (Cashiers) in the most highly concentrated markets. The average of these three point estimates is 0.564%. This implies that, for the average county in the data, a 10 cent increase in the minimum wage decreases larceny-theft incidents by 4.5.[13] If I assume that the mechanism driving the effect of the minimum wage on crime is entirely an employment effect, for the average county we see a decrease in 0.81 larceny-theft incidents per every additional individual employed. These results are consistent with hypothesis 2. The results without crime controls in Tables 4 and 5 are similar.

The results for burglary (Tables 6 and 7 without crime controls and Tables 14 and 15 with crime controls) are consistent with theory but not statistically

[12] These results are my "first stage" results; they are supposed to replicate Azar, Huet-Vaughn, et al. (2019) exactly. The results are indeed similar, but they do not match exactly. This seems to be due to a difference in HHI measures in my paper compared to theirs. I have been in touch with the authors about replication, and believe that this discrepancy is due to an update in the Lightcast data.

[13] Note that this is likely a lower bound estimate on the effect of the minimum wage on the number of larceny-theft incidents for the average county, since not all larceny-theft are reported to the police and the data does not contain crime reports from all law-enforcement agencies.

significant in general, so I do not focus on them here. The same is true for motor-vehicle theft (Tables 8 and 9 without crime controls and Tables 16 and 17 with crime controls).

I conduct placebo regressions by estimating equations 8 and 9 with violent crime as the dependent variable. The rationale for these placebo regressions is that the minimum wage should not affect crimes that are not property crimes. I observe no statistically significant effects of the minimum wage on violent crime (Tables 19 and 20). Note that these regressions include all crime controls except the control for the log of violent crime. The point estimates in these tables are typically positive (but not statistically significant), which is the opposite sign of the point estimates for property crimes.

I conduct several important robustness checks. First, I include a rich set of demographic control variables (in addition to the baseline controls and crime controls): the fraction male, the fraction white, and the fraction in various age categories. The results are similar and presented in Appendix Tables A2-A9. I also re-calculate the HHI measure using the first two years of data (2010-2011) and then estimate equations 8 and 9 using data from 2012-2016. The results are similar and presented in Appendix Tables A10-17.

6. Conclusion

This paper investigates how local labor market concentration moderates the effect of the minimum wage on property crime. I show that, in a simple theoretical framework that combines insights from a Becker-Ehrlich model of crime with insights from a Cournot model of labor demand, the effect of the minimum wage on crime is unambiguously negative when labor markets are highly concentrated and the magnitude of the effect of the minimum wage on crime is larger when market concentration is higher. To test this theory, I combine administrative crime data from the FBI's Uniform Crime Reporting (UCR) program with firm-level data from Lightcast. I use a two-way fixed effects model, similar to Azar, Huet-Vaughn, et al. (2019). Ultimately, I find that the minimum wage decreases larceny-theft when labor markets are concentrated, and that the magnitude of this negative effect increases when market concentration increases. My results have important implications for policymakers, since they suggest that the minimum wage has spill-over effects on local property crime rates and that the degree of local labor market concentration moderates the effect of the minimum wage on crime.

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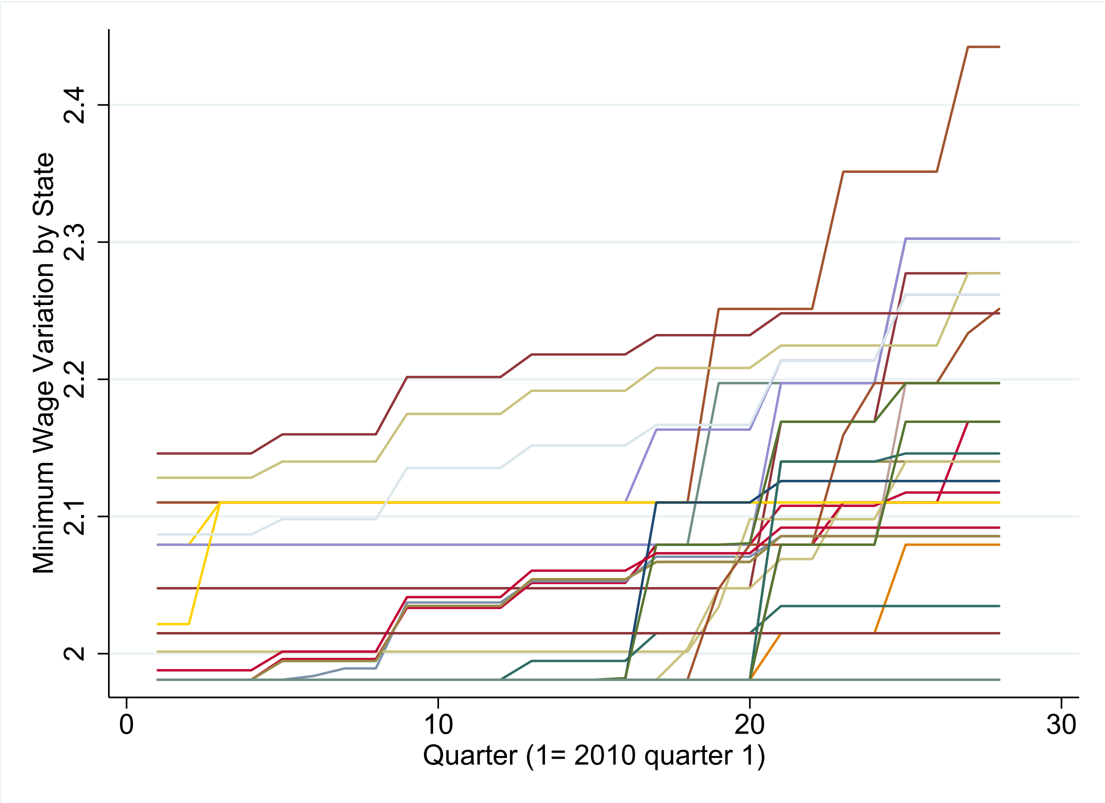
Figure 1: Minimum wage changes over sample period



Note: This figure plots the state-level minimum wage (equal to the maximum of the state and federal minimum wages in each state) from 2010 Q1 to 2016 Q4. Each line in the graph corresponds to one state in the data.

Figure 2: Histogram for Cashiers HHI (SOC 412011)

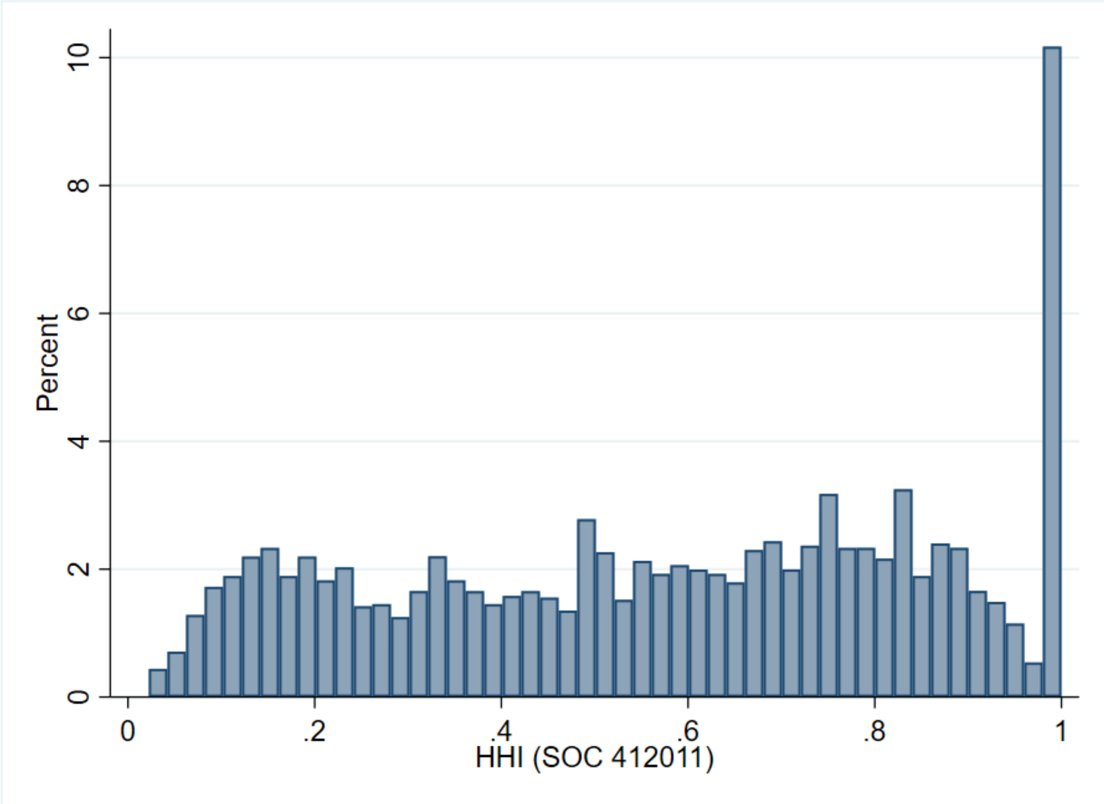


Figure 3: Histogram for Retail Sales HHI (SOC 412031)

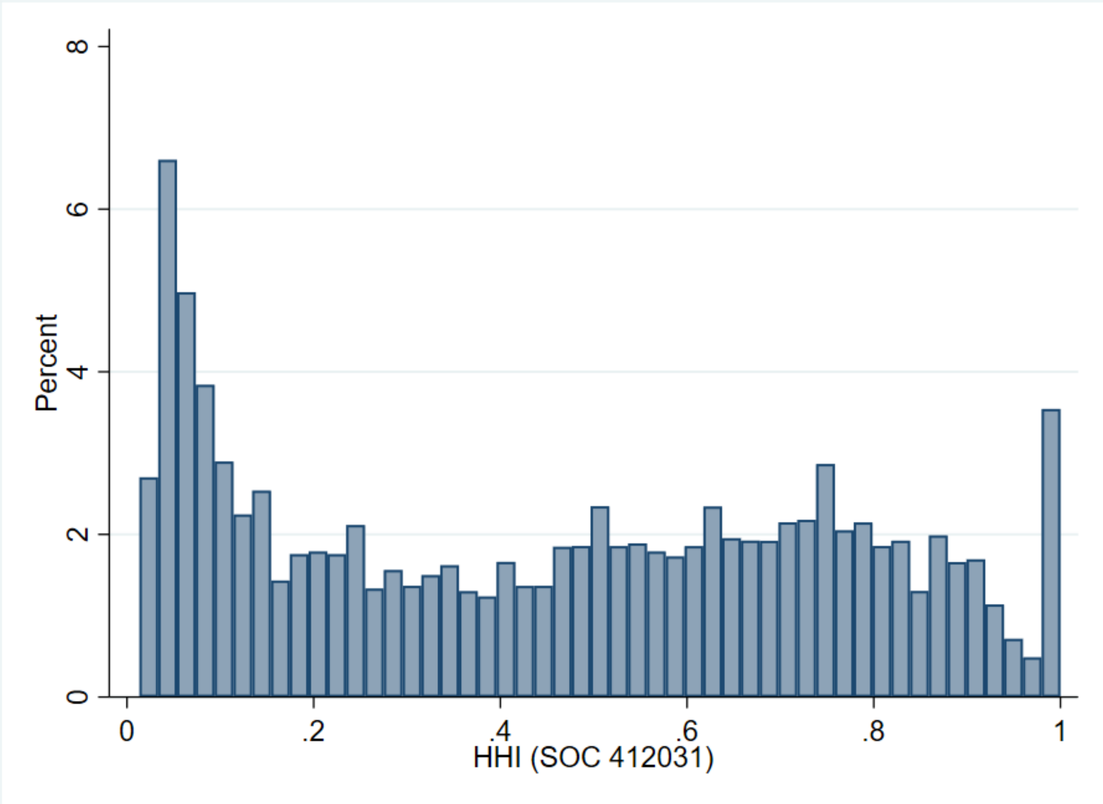


Figure 4: Histogram for Stock Clerks HHI (SOC 435081)

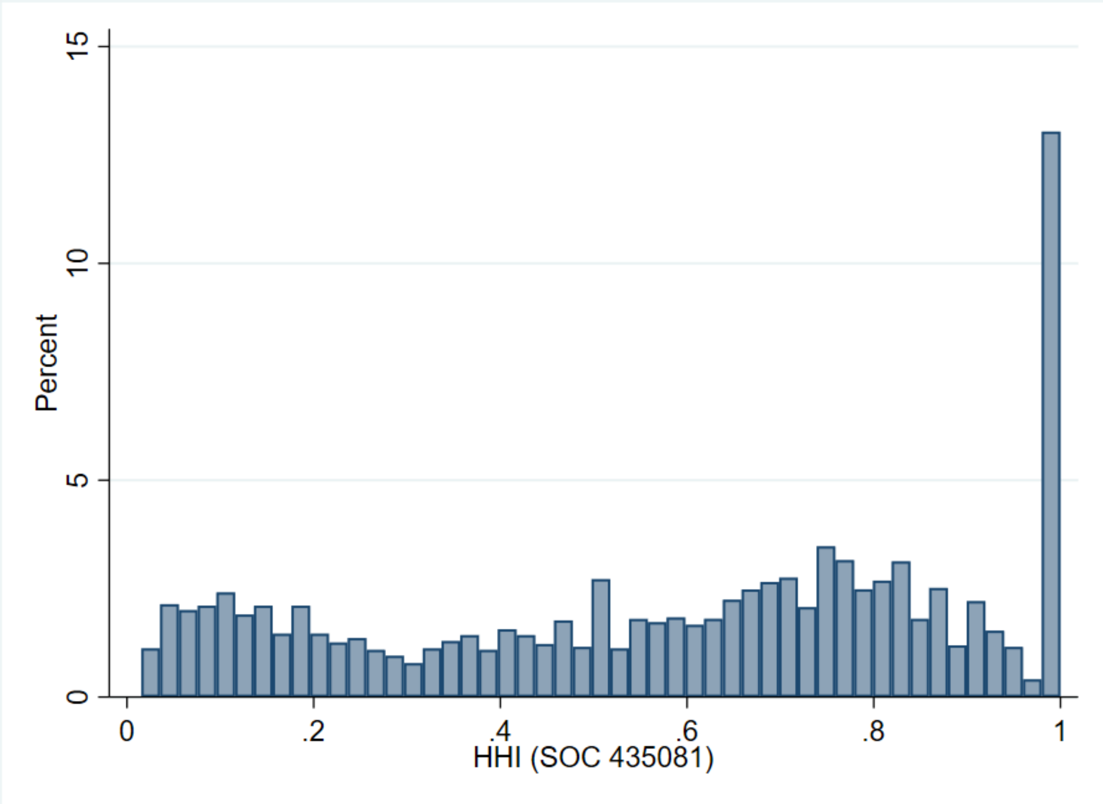


Table 1: Summary statistics

VARIABLES	(1) mean	(2) sd	(3) min	(4) max
max(fed mw, state mw)	7.508	0.510	7.250	11.50
Avg HHI (Cashiers)	0.555	0.290	0.0223	1
Avg HHI (Stock Clerks)	0.565	0.309	0.0154	1
Avg HHI (Retail Sales)	0.437	0.308	0.0133	1
theft	601.1	1,811	0	40,248
burglary	190.8	597.1	0	13,417
mvt	77.28	379.9	-1	12,915
violent crime	121.4	488.8	-2	14,832
NAICS452 emp.	1,116	3,038	0	79,477
tot. earnings (millions)	474.6	2,078	0	80,936
total emp. (thousands)	50.37	155.8	0	4,751
population (thousands)	110.0	338.5	0	10,106
unemp. rate	7.187	2.960	1.100	29.40
property clearance rate	0.215	0.140	0	2.227
violent clearance rate	0.539	0.278	-3	5.522
fraction white	0.860	0.164	0.0327	1
fraction aged 15-24	0.130	0.0342	0.0426	0.487
fraction aged 25-34	0.118	0.0214	0.0538	0.283
fraction aged 35-44	0.117	0.0154	0.0531	0.204
fraction aged 45-54	0.139	0.0158	0.0452	0.244
fraction aged 55-64	0.137	0.0212	0.0276	0.250
fraction aged 65+	0.170	0.0447	0.0348	0.563
fraction male	0.500	0.0224	0.429	0.726

Note: This table contains summary statistics for the variables used in the analyses. Clearance rates are reported per crime committed. Crimes and clearance rates can be negative in rare instances due to data clean-up by the law-enforcement agency (Kaplan, 2023). Clearance rates can be greater than 1 if more than one individual is arrested for the same crime.

Table 2: Minimum Wage Effect on Employment by Concentration in Occupational Labor Market

Dependent variable: log(employment)

	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	-0.271**	-0.221***	-0.288**
	(0.102)	(0.0701)	(0.115)
log(mw) * Avg HHI	0.640***	0.837***	0.692***
	(0.203)	(0.217)	(0.249)
Observations	56,953	57,489	56,913
R-squared	0.994	0.994	0.994
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log employment in the retail sector (NAICS 452). Standard errors are clustered at the state level. See main text for details.

Table 3: Minimum Wage Effect on Employment by Concentration in Occupational Labor Market

Dependent variable: log(employment)

	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	-0.163*	-0.187**	-0.180**
	(0.0868)	(0.0761)	(0.0861)
log(mw) * High HHI	0.264***	0.478***	0.299***
	(0.0765)	(0.0924)	(0.0746)
Observations	56,953	57,489	56,913
R-squared	0.994	0.995	0.994
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log employment in the retail sector (NAICS 452). Standard errors are clustered at the state level. See main text for details.

Table 4: Minimum Wage Effect on Larceny-Theft by Concentration in Occupational Labor Market

	Dependent variable: log(theft)		
	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.380**	0.303**	0.477***
	(0.145)	(0.139)	(0.137)
log(mw) * Avg HHI	-0.647***	-0.588**	-0.771***
	(0.228)	(0.283)	(0.264)
Observations	63,128	63,888	63,146
R-squared	0.963	0.963	0.963
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log larceny-theft rate. Standard errors are clustered at the state level. See main text for details.

Table 5: Minimum Wage Effect on Larceny-Theft by Concentration in Occupational Labor Market

	Dependent variable: log(theft)		
	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.406***	0.373***	0.464***
	(0.129)	(0.133)	(0.124)
log(mw) * High HHI	-0.373***	-0.389***	-0.399***
	(0.0909)	(0.130)	(0.0848)
Observations	64,006	64,806	64,064
R-squared	0.963	0.963	0.963
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log larceny-theft rate. Standard errors are clustered at the state level. See main text for details.

Table 6: Minimum Wage Effect on Burglary by Concentration in Occupational Labor Market

Dependent variable: log(burg)			
	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.268	0.250	0.292*
	(0.203)	(0.165)	(0.165)
log(mw) * Avg HHI	-0.111	-0.00625	-0.0995
	(0.324)	(0.329)	(0.309)
Observations	62,561	63,299	62,556
R-squared	0.933	0.933	0.933
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log burglary rate. Standard errors are clustered at the state level. See main text for details.

Table 7: Minimum Wage Effect on Burglary by Concentration in Occupational Labor Market

Dependent variable: log(burg)			
	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.278*	0.337**	0.266
	(0.163)	(0.152)	(0.162)
log(mw) * High HHI	-0.0891	-0.194	-0.0297
	(0.149)	(0.157)	(0.145)
Observations	62,561	63,299	62,556
R-squared	0.933	0.933	0.933
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log burglary rate. Standard errors are clustered at the state level. See main text for details.

Table 8: Minimum Wage Effect on Motor-Vehicle Theft by Concentration in Occupational Labor Market

Dependent variable: log(mvt)			
	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.144	0.131	0.182
	(0.275)	(0.210)	(0.253)
log(mw) * Avg HHI	-0.320	-0.381	-0.352
	(0.385)	(0.326)	(0.360)
Observations	56,991	57,570	56,999
R-squared	0.915	0.915	0.915
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log motor-vehicle theft rate. Standard errors are clustered at the state level. See main text for details.

Table 9: Minimum Wage Effect on Motor-Vehicle Theft by Concentration in Occupational Labor Market

Dependent variable: log(mvt)			
	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.0883	0.203	0.102
	(0.244)	(0.219)	(0.246)
log(mw) * High HHI	-0.124	-0.422**	-0.113
	(0.214)	(0.200)	(0.193)
Observations	56,991	57,570	56,999
R-squared	0.915	0.915	0.915
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log motor-vehicle theft rate. Standard errors are clustered at the state level. See main text for details.

Table 10: Minimum Wage Effect on Employment by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(emp)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	-0.321***	-0.266***	-0.326***
	(0.103)	(0.0783)	(0.115)
log(mw) * Avg HHI	0.754***	1.055***	0.758***
	(0.226)	(0.231)	(0.253)
Observations	44,320	44,493	44,368
R-squared	0.994	0.994	0.994
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log employment in the retail sector (NAICS 452). Standard errors are clustered at the state level. See main text for details.

Table 11: Minimum Wage Effect on Employment by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(emp)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	-0.185**	-0.203***	-0.207**
	(0.0800)	(0.0736)	(0.0783)
log(mw) * High HHI	0.248***	0.518***	0.293***
	(0.0799)	(0.101)	(0.0765)
Observations	44,320	44,493	44,368
R-squared	0.994	0.994	0.994
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log employment in the retail sector (NAICS 452). Standard errors are clustered at the state level. See main text for details.

Table 12: Minimum Wage Effect on Larceny-Theft by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(larceny-theft)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.338***	0.227*	0.462***
	(0.123)	(0.129)	(0.163)
log(mw) * Avg HHI	-0.988***	-1.056***	-1.149***
	(0.229)	(0.254)	(0.201)
Observations	59,035	59,929	59,121
R-squared	0.810	0.810	0.810
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log larceny-theft rate. Standard errors are clustered at the state level. See main text for details.

Table 13: Minimum Wage Effect on Larceny-Theft by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(larceny-theft)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.249**	0.188*	0.317**
	(0.118)	(0.112)	(0.127)
log(mw) * High HHI	-0.530***	-0.603***	-0.558***
	(0.0986)	(0.127)	(0.0921)
Observations	59,035	59,929	59,121
R-squared	0.810	0.811	0.810
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log larceny-theft rate. Standard errors are clustered at the state level. See main text for details.

Table 14: Minimum Wage Effect on Burglary by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(burg)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.312*	0.233*	0.395***
	(0.176)	(0.135)	(0.147)
log(mw) * Avg HHI	-0.370	-0.146	-0.465**
	(0.325)	(0.300)	(0.229)
Observations	55,028	55,626	55,107
R-squared	0.944	0.944	0.944
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log burglary rate. Standard errors are clustered at the state level. See main text for details.

Table 15: Minimum Wage Effect on Burglary by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(burg)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.302**	0.284**	0.317**
	(0.140)	(0.121)	(0.137)
log(mw) * High HHI	-0.232*	-0.217	-0.192
	(0.127)	(0.143)	(0.118)
Observations	55,028	55,626	55,107
R-squared	0.944	0.944	0.944
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log burglary rate. Standard errors are clustered at the state level. See main text for details.

Table 16: Minimum Wage Effect on Motor-Vehicle-Theft by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(mvt)

	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.181	0.168	0.209
	(0.272)	(0.210)	(0.259)
log(mw) * Avg HHI	-0.443	-0.553	-0.432
	(0.392)	(0.382)	(0.377)
Observations	51,862	52,361	51,933
R-squared	0.921	0.920	0.921
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log motor-vehicle theft rate. Standard errors are clustered at the state level. See main text for details.

Table 17: Minimum Wage Effect on Motor-Vehicle-Theft by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(mvt)

	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.112	0.221	0.131
	(0.245)	(0.209)	(0.244)
log(mw) * High HHI	-0.180	-0.501**	-0.165
	(0.226)	(0.206)	(0.205)
Observations	51,862	52,361	51,933
R-squared	0.921	0.920	0.921
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log motor-vehicle theft rate. Standard errors are clustered at the state level. See main text for details.

Table 18: Minimum Wage Effect on Violent Crime by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(violent)			
	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.0385	0.0876	-0.0989
	(0.183)	(0.188)	(0.240)
log(mw) * Avg HHI	0.729	1.016	1.066
	(0.536)	(0.803)	(0.684)
Observations	55,291	55,904	55,378
R-squared	0.937	0.937	0.937
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 8 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log violent crime rate. Standard errors are clustered at the state level. See main text for details.

Table 19: Minimum Wage Effect on Violent Crime by Concentration in Occupational Labor Market (with crime controls)

Dependent variable: log(violent)			
	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.203	0.297	0.120
	(0.223)	(0.187)	(0.214)
log(mw) * High HHI	0.475	0.523	0.591*
	(0.342)	(0.371)	(0.318)
Observations	61,678	62,440	61,760
R-squared	0.926	0.925	0.926
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓

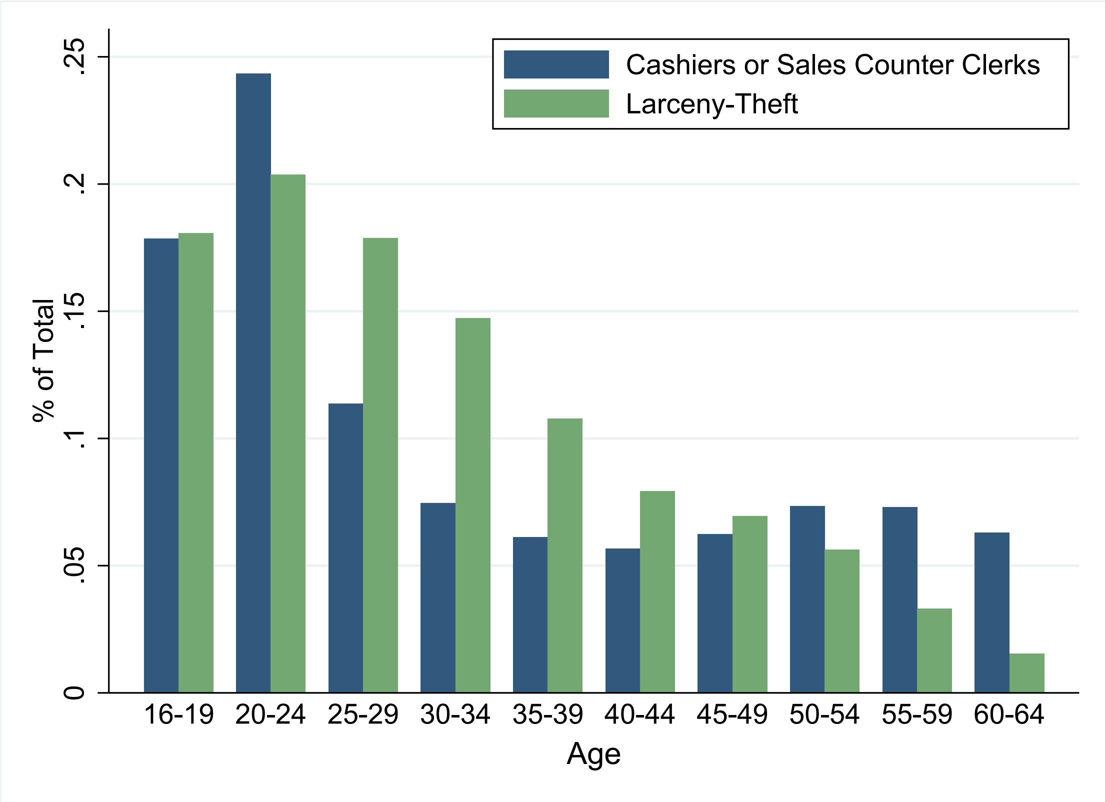
*** p<0.01, ** p<0.05, * p<0.1

Note: This table shows the results from the estimation of equation 9 for the occupational labor markets: Stock Clerks, Retail Sales, and Cashiers. The dependent variable is log violent crime rate. Standard errors are clustered at the state level. See main text for details.

Appendices

Tables and Figures

Figure A1: Comparison of the Age Distributions of OCC275/276 and Larceny-Theft



Note: This figure compares the age distribution of individuals employed in selected retail occupations with the age distribution of individuals arrested for larceny-theft. Plotted in blue are the fraction of workers in occupations OCC275 (Sales Counter Clerks) or OCC276 (Cashiers) in each age category. Plotted in green are the fraction of arrests for larceny-theft in each age category. All data are for the year 2015. Occupation data come from the American Community Survey (ACS) and crime data come from the FBI's Uniform Crime Reporting (UCR) Program (Kaplan, 2019b).

Table A1: Data sources and variable descriptions

Variable	Description	Source
Minimum wage	Indep.	Allegretto et al. (2017)
Minimum wage [2015-2016]	Indep.	Hand-collected
Market concentration (HHI)	Indep.	Lightcast
Larceny-theft	Dep.	Kaplan (2019b)
Employment [NAICS 452]	Dep.	QCEW
Unemployment rate	Azar et al. Control	LAUS
Total earnings	Azar et al. Control	QCEW
Total employed	Azar et al. Control	LAUS
Clearance rates	Crime Control	Kaplan (2019a)
Violent crime rate	Crime Control	Kaplan (2019a)
Demographic variables	Demogr. Control	NBER [originally SEER]

Note: This table contains data sources and a brief description of the variables used in the main analyses. See Section 4 and equation 8 for the empirical specification. 'Indep.' refers to the main independent variables. Dep.' refers to the main dependent variables. Control variables are split into three categories: 'Azar et al. Control', 'Crime Control', and 'Demographic Control'. The 'Azar et al. Control' variables are the same control variables (with the same sources) as those that appear in Azar, Huet-Vaughn, et al. (2019). The 'Crime Control' variables are additional control variables relevant to the analysis in this paper, as informed by the literature. The 'Demographic Control' variables are (1) the fraction within the following age categories: 16-24, 25-34, 35-44, 45-54, 55-64, and 65+ (0-15 is the omitted age category in the regression); (2) the fraction white ('non-white' is the omitted race category); and (3) the fraction male ('female' is the omitted sex category). 'LAUS' refers to the BLS Local Area Unemployment Statistics (LAUS). 'NBER' is the National Bureau of Economic Research which makes available cleaned and compiled demographic data from 'SEER' (Survey of Epidemiology and End Results).

Table A2: Minimum Wage Effect on Employment by Concentration in Occupational Labor Market (with demographic controls)

Dependent variable: log(emp)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	-0.288***	-0.247***	-0.299**
	(0.106)	(0.0812)	(0.116)
log(mw) * Avg HHI	0.676***	0.991***	0.700***
	(0.231)	(0.237)	(0.249)
Observations	44,286	44,459	44,334
R-squared	0.994	0.994	0.994
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓
Demographic controls	✓	✓	✓

Table A3: Minimum Wage Effect on Employment by Concentration in Occupational Labor Market (with demographic controls)

Dependent variable: log(emp)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	-0.161*	-0.191**	-0.186**
	(0.0818)	(0.0760)	(0.0808)
log(mw) * High HHI	0.213**	0.499***	0.266***
	(0.0816)	(0.107)	(0.0804)
Observations	44,286	44,459	44,334
R-squared	0.994	0.994	0.994
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓
Demographic controls	✓	✓	✓

Table A4: Minimum Wage Effect on Larceny-theft by Concentration in Occupational Labor Market (with demographic controls)

Dependent variable: log(theft)

	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.370**	0.236*	0.464***
	(0.151)	(0.126)	(0.140)
log(mw) * Avg HHI	-0.864***	-0.708***	-0.975***
	(0.193)	(0.206)	(0.210)
Observations	55,218	55,829	55,310
R-squared	0.973	0.972	0.973
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓
Demographic controls	✓	✓	✓

Table A5: Minimum Wage Effect on Larceny-theft by Concentration in Occupational Labor Market (with demographic controls)

Dependent variable: log(theft)

	(1)	(2)	(3)
VARIABLES	Stock Clerks	Retail Sales	Cashiers
log(mw)	0.326**	0.231*	0.385***
	(0.138)	(0.121)	(0.136)
log(mw) * High HHI	-0.508***	-0.457***	-0.529***
	(0.0936)	(0.0967)	(0.0926)
Observations	55,218	55,829	55,310
R-squared	0.973	0.973	0.973
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓
Demographic controls	✓	✓	✓

Table A6: Minimum Wage Effect on Burglary by Concentration in Occupational Labor Market (with demographic controls)

Dependent variable: log(burg)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.303*	0.211*	0.384***
	(0.159)	(0.123)	(0.133)
log(mw) * Avg HHI	-0.434	-0.197	-0.521**
	(0.280)	(0.262)	(0.197)
Observations	54,994	55,592	55,073
R-squared	0.944	0.944	0.944
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓
Demographic controls	✓	✓	✓

Table A7: Minimum Wage Effect on Burglary by Concentration in Occupational Labor Market (with demographic controls)

Dependent variable: log(burg)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.302**	0.260**	0.305**
	(0.130)	(0.117)	(0.129)
log(mw) * High HHI	-0.288**	-0.248**	-0.228**
	(0.109)	(0.122)	(0.0980)
Observations	54,994	55,592	55,073
R-squared	0.944	0.944	0.944
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓
Demographic controls	✓	✓	✓

Table A8: Minimum Wage Effect on Motor-Vehicle Theft by Concentration in Occupational Labor Market (with demographic controls)

Dependent variable: log(mvt)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.115	0.0976	0.127
	(0.259)	(0.203)	(0.246)
log(mw) * Avg HHI	-0.407	-0.499	-0.369
	(0.364)	(0.364)	(0.360)
Observations	51,831	52,330	51,902
R-squared	0.921	0.921	0.921
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓
Demographic controls	✓	✓	✓

Table A9: Minimum Wage Effect on Motor-Vehicle Theft by Concentration in Occupational Labor Market (with demographic controls)

Dependent variable: log(mvt)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.0554	0.162	0.0554
	(0.239)	(0.205)	(0.232)
log(mw) * High HHI	-0.172	-0.495**	-0.134
	(0.218)	(0.195)	(0.186)
Observations	51,831	52,330	51,902
R-squared	0.921	0.921	0.921
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓
Demographic controls	✓	✓	✓

Table A10: Minimum Wage Effect on Employment by Concentration in Occupational Labor Market (pre-determined HHI)

Dependent variable: log(emp)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	-0.271**	-0.231**	-0.279**
	(0.105)	(0.0915)	(0.124)
log(mw) * Avg HHI	0.386***	0.425***	0.405*
	(0.142)	(0.140)	(0.210)
Observations	37,940	42,022	38,250
R-squared	0.993	0.993	0.994
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Table A11: Minimum Wage Effect on Employment by Concentration in Occupational Labor Market (pre-determined HHI)

Dependent variable: log(emp)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	-0.155*	-0.162**	-0.146
	(0.0899)	(0.0772)	(0.0933)
log(mw) * High HHI	0.145**	0.205**	0.130*
	(0.0554)	(0.0788)	(0.0684)
Observations	37,940	42,022	38,250
R-squared	0.993	0.993	0.994
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Table A12: Minimum Wage Effect on Larceny-Theft by Concentration in Occupational Labor Market (pre-determined HHI)

Dependent variable: log(theft)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.686***	0.394**	0.721***
	(0.170)	(0.160)	(0.158)
log(mw) * Avg HHI	-0.981***	-0.810***	-1.072***
	(0.228)	(0.184)	(0.161)
Observations	43,454	50,351	44,175
R-squared	0.975	0.973	0.975
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Table A13: Minimum Wage Effect on Larceny-Theft by Concentration in Occupational Labor Market (pre-determined HHI)

Dependent variable: log(theft)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.357**	0.372**	0.436**
	(0.152)	(0.160)	(0.168)
log(mw) * High HHI	-0.339***	-0.599***	-0.446***
	(0.105)	(0.120)	(0.110)
Observations	43,454	50,351	44,175
R-squared	0.975	0.973	0.975
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Table A14: Minimum Wage Effect on Burglary by Concentration in Occupational Labor Market (pre-determined HHI)

Dependent variable: log(burg)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.172	0.302**	0.349*
	(0.177)	(0.142)	(0.186)
log(mw) * Avg HHI	-0.0423	-0.474*	-0.334
	(0.251)	(0.260)	(0.262)
Observations	43,354	50,219	44,086
R-squared	0.950	0.946	0.950
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Table A15: Minimum Wage Effect on Burglary by Concentration in Occupational Labor Market (pre-determined HHI)

Dependent variable: log(burg)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.202	0.240*	0.380**
	(0.178)	(0.136)	(0.175)
log(mw) * High HHI	-0.0675	-0.270*	-0.278
	(0.156)	(0.148)	(0.173)
Observations	43,354	50,219	44,086
R-squared	0.950	0.946	0.950
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Table A16: Minimum Wage Effect on Motor-Vehicle Theft by Concentration in Occupational Labor Market (pre-determined HHI)

Dependent variable: log(mvt)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	0.00571	0.153	0.0869
	(0.349)	(0.246)	(0.329)
log(mw) * Avg HHI	-0.126	-0.376	-0.353
	(0.444)	(0.305)	(0.421)
Observations	41,786	48,025	42,509
R-squared	0.930	0.923	0.929
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1

Table A17: Minimum Wage Effect on Motor-Vehicle Theft by Concentration in Occupational Labor Market (pre-determined HHI)

Dependent variable: log(mvt)

VARIABLES	(1) Stock Clerks	(2) Retail Sales	(3) Cashiers
log(mw)	-0.368	0.0884	-0.272
	(0.348)	(0.243)	(0.376)
log(mw) * High HHI	0.363	-0.182	0.170
	(0.288)	(0.239)	(0.338)
Observations	41,786	48,025	42,509
R-squared	0.930	0.923	0.929
County FE	✓	✓	✓
Census division period FE	✓	✓	✓
State-specific time trends	✓	✓	✓
Azar et al. controls	✓	✓	✓
Crime controls	✓	✓	✓

*** p<0.01, ** p<0.05, * p<0.1