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Consumption and geographic mobility in pandemic times: Evidence from Mexico[1]

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We analyze the universe of point-of-sale (POS) transactions before and during the COVID-19 lockdown in Mexico. We find three key results. First, consumption in Mexico fell by 23 percent in the April-June quarter of 2020. Second, reductions in consumption were highly heterogeneous across sectors and states, with states and activities related to tourism the most affected. Third, using variation over time and states, we estimate the elasticity of POS expenditures with respect to geographic mobility (measured using cellphone location data) to be slightly less than 1. This estimate suggests that spending in developing countries may be more responsive to mobility than in developed countries, and that mobility indicators could be used as a real-time proxy for consumption in some economies.

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1. Introduction

The economic consequences of COVID-19 are significant. Lockdown and health measures have substantially decreased geographic mobility, causing a drop in economic activity. The traditional economic indicators that measure these effects, like gross domestic product (GDP) and the industrial production index (IPI) are published by national statistical agencies with a lag: in Mexico, approximately two months after the fact. Researchers and policy-makers across the world are trying to overcome this delay by analyzing high-frequency data to quantify the magnitude of the shock and make prescriptions to avoid a more severe economic contraction (see, for example, the weekly economic index of Lewis, Mertens, and Stock 2020; the index of expenditures of Baker et al. 2020; and the labor market index of Kahn, Lange, and Wiczer 2020). Given the possibility of future waves of COVID-19, it is extremely important to measure the relationship of mobility and economic activity. In this paper, we use aggregated daily point-of-sale (POS) transaction data and cellphone location data in Mexico to quantify the magnitude of the shock and to estimate the effect of mobility patterns on POS expenditures.

It is now well known that a supply shock may cause a demand shock in the economy, thus amplifying the initial economic impact (Guerrieri et al. 2020). Sectors related to services, such as restaurants and tourism, are directly affected by a pandemic. One could then expect that the total shock should be proportional to the income losses of these sectors. However, income generated in other sectors may be affected as well, depending on the value of current versus future consumption and the value of goods and services not provided during the pandemic. If we have a high intertemporal elasticity of substitution (e.g., people can modify their consumption patterns relatively easily to spend more later rather than now) and a low intra-temporal elasticity of substitution (e.g., people prefer to buy the same goods and services, and there are no good substitutes for their consumption patterns), then a demand shock exacerbates the original shock, which can present an even greater problem in the presence of uncertainty and incomplete markets.

It is thus important to estimate how total expenditure is changing over time and which sectors are most affected, an estimate that requires high frequency data. POS expenditure data may meet the requirements for such analysis. Indeed, there are recent articles that make use of such information. In the United States, Baker et al. (2020) use de-identified non-random data from a Fintech company at the transaction and individual level. They find a spike in total spending when cases begin to increase (late February and early March) but a subsequent decrease of close to 50 percent with respect to January and early February. In Spain, Carvalho et al. (2020) use all POS transactions of customers of a commercial bank and transactions of others using the POS terminals of that bank. As in the U.S. study, they find a spike before the mid-March lockdown and then a sharp decline in total expenditure: 60 percent with respect to the same period in 2019. In Denmark, Andersen et al. (2020a) use data from the country's largest retail bank. They find a decrease in total spending of around 25 percent after lockdown starts. Similar results have been found in other countries: the United Kingdom shows a decline of 46 percent from April 2019 to April 2020 (Hacioglu, Känzig, and Surico 2020), France a decline of 60 percent (Bounie, Camara, and Galbraith 2020), Portugal a reduction of 55 percent in total purchases in April (Carvalho, Peralta, and Pereira 2020), and China a decline of 42 percent (Chen, Qian, and Wen 2020).

POS data is useful for shedding light on causes and potential solutions for the current crisis. Using U.S. data, Chetty et al. (2020) argue that the drop in POS expenditures is driven mainly by rich households due to health concerns. Expenditures in poor households generally returned to 2019 levels after their stimulus payments arrived.

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Employment losses are greater in higher-income zip codes, especially in personal services like restaurants and barber shops. They conclude that economic recovery goes hand in hand with safety concerns.

Our paper makes important contributions to this literature. First, we show that the response in developing countries may be different than in developed countries. Although Mexico is an upper middle-income country, its financial sector is not as developed as in other countries. According to the World Bank (2020), domestic bank credit to the private sector accounts for only 27 percent of GDP, while in countries with similar consumption patterns, like China, Denmark, France, Spain, and the United Kingdom, it is close to or above 100 percent. Only in the United States is it less than that, and even there it is 52 percent of GDP. Also, the number of POS terminals in Mexico per 100,000 population is the lowest among similar countries (approximately 1000 in Mexico versus 2000 in China and 3000 in the other countries). Finally, internet penetration in Mexico (around 64 percent) is less than in the United States (76 percent) or similar European countries (all above 80 percent). Although this may mean that POS data are not as comprehensive for Mexico, our results indicate large negative effects of the pandemic, although not as large as in those in other countries.

Second, the data we analyze for Mexico includes all POS transactions in the country, in contrast to the data in previous studies, which is limited to selected banks or companies. The comprehensive nature of our data allows us to benchmark the effect of COVID-19 on POS expenditures to traditional measures like total consumption and GDP. Third, although we follow previous literature in calculating expenditure losses with respect to 2019, we also propose a simple model to calculate a counterfactual of what expenditure would have looked like in the absence of the pandemic. Finally, we estimate the elasticity of POS expenditures with respect to measures of geographic mobility using

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variation over time within states in Mexico. This elasticity is important, as it could be used in theoretical models and simulation exercises to calculate expenditure losses for future waves of the pandemic. It is also an important consideration in the debate about the impact of lockdown measures on the level of expenditures.

We use the universe of point-of-sale (POS) transactions from January 1, 2019 to June 30, 2020, which is non-public data from the Banco de México (the Mexican central bank), consisting of aggregated daily information on total expenditures and certain other categories. This POS expenditure data provides important information about general consumption patterns. In 2019, there were 157 million debit and credit cards in Mexico, and the National Financial Inclusion Survey (INEGI, 2018) shows that more than two-thirds of the Mexican population (68 percent) aged 18-70 have at least one such financial product. In 2019, the average POS expenditure per transaction was $630 MXN (approximately $31 USD). Approximately 10 million transactions take place through POS terminals every day, 73 percent of which are with debit cards and the remaining 27 percent with credit cards. The average monthly total debit and credit card expenditure was almost $187 billion MXN during 2019 (approximately $9.2 billion USD). Annual total POS expenditure thus represents about 8 percent of GDP and 14 percent of consumption.

We are able to provide the first direct estimates of the elasticity of POS expenditures with respect to geographic mobility. Previous studies have provided only indirect or implicit estimates for this elasticity. For example, using the results in Andersen et al. (2020b), we can estimate an elasticity of 0.2 by exploiting the between-country variation in spending and mobility for Sweden and Denmark: consumption declined 29 percent in Denmark and by 25 percent in Sweden (Figure 3 in that study). Using mobility measures based on cellphone location data available from the Apple Corporation (2020)

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for early April, we find that mobility decreased by only 12 percent in Sweden while it declined by 32 percent in Denmark. The implicit elasticity of POS expenditures with respect to mobility is thus around 0.2. In the current study, since we have daily data for expenditures in Mexico at the subnational level, we are able to estimate the elasticity of consumption with respect to mobility indicators by exploiting both the time and geographic variation in the data.

We find three key results. First, the percent loss in POS expenditures with respect to the estimate without the pandemic is 23 percent for April-June. This estimate is much lower than that for other countries. The estimate for Spain and France (for the last two weeks of March) is close to 50 percent (Bounie et al. 2020; Carvalho et al. 2020), for Portugal it is 55 percent (Carvalho, Peralta, and Pereira 2020), and for Denmark it is 30 percent (Andersen et al. 2020a). Although estimates for the U.S. vary, our result is similar to the live results from POS data in Chetty et al. (2020). In terms of GDP and consumption, for the April-June quarter it implies a loss of 2.6 percent of quarterly GDP and 3.9 percent of quarterly private consumption.

Second, losses vary significantly across sectors and regions. While some sectors were severely hit, like tourism, food services, and transportation, others, like insurance and telecommunications, were barely affected. This result is similar to that found in other studies. Mexican states that are highly dependent on tourism (beach resorts and other tourist destinations) are among the most affected.

Third, we estimate the elasticity of POS expenditures with respect to geographic mobility in Mexico, as measured using cellphone location data from Apple (2020) and Google (2020). Our estimates show that this elasticity is in most cases non-significantly different from one (0.93 using Apple's measure of mobility in one specification, and 0.91 for both Google's and Apple's measures of mobility in another). These estimates are

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much larger and more precisely estimated than the estimate of 0.2 derived by comparing the effect of mobility on spending in Sweden and Denmark, as described above. This result suggests that POS expenditures in developing countries could be more responsive to mobility patterns than in developed countries, an interesting possibility that calls for further research. It may be possible, for example, that internet penetration and the strength of e-commerce affect the magnitude of this elasticity. This result is also important because it suggests that in economies like Mexico's, mobility indicators, which can be observed almost in real time, could serve as a good proxy for the behavior of expenditures.

2. Data and Methods

The data includes all point-of-sale (POS) transactions in Mexican territory, which is non-public information collected by the Banco de México under its mandate to assure a well-functioning payment system. The data is aggregated by type of card (debit or credit), at the state and national levels, and by type of expenditure, on a daily basis, from January 2019 to June 2020. We observe only aggregate information; we do not observe any individual transactions, any information about whether the credit or debit card is foreign or Mexican, or whether the transaction took place on the internet or in a physical location.

Most of the previous literature uses either a part of the universe of transactions or a sample of households. Our use of the full universe of transactions allows us to calculate total losses in the economy. However, one key challenge is how to construct a valid counterfactual for comparison. In general, previous studies calculate the percent change in 2020 with respect to 2019. This seems reasonable if the financial sector is stable. However, because transactions in Mexico were already growing before the pandemic arrived it seems more appropriate to construct a counterfactual scenario using data from

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2019 and 2020. We propose a simple model that predicts the daily (t) outcome in 2020 (POS_t^{2020}) based on both the 2019 outcome (POS_t^{2019}) and pre-pandemic data observed for 2020.[1] We also include dummy variables related to paydays, Mondays, Fridays, and for the month of December.

$$POS_t^{2020} = \alpha + \beta POS_t^{2019} + dummies + \varepsilon_t \tag{1}$$

The regression is estimated for all days from January 1, 2020 to February 18, 2020. We select the final model minimizing the mean squared error for the prediction for February 19 to March 11, 2020, that is, during the pre-lockdown period. Then, we make a prediction for all the remaining days in 2020. All of the predictions are in constant pesos (MXN) of July 2018. The percent effect of the pandemic can then be calculated as:

$$\Delta\%\ Effect_t = \frac{POS_t^{2020} - \widehat{POS}_t^{2020}}{\widehat{POS}_t^{2020}} \tag{2}$$

The comparison with respect to 2019 replaces the predicted value $\widehat{POS}_t^{2020}$ with the value in 2019, POS_t^{2019}. As the daily expenditures are noisy, in some cases we smooth the lines in the figures by a simple moving average for the previous two weeks. We show below multiple estimates for total expenditures, for credit and debit cards, for type of expenditure, and at the state level.

We also calculate the elasticity of total expenditures with respect to indicators of geographic mobility, obtained from Google (2020) and Apple (2020). Google tracks mobility using the location history of the Google accounts on people's mobile devices; we use this data to calculate the percent change compared with the median value for baseline days in the five-week period January 3 to February 6, 2020. We focus on the mobility trends for workplaces. Apple mobility is an index with a baseline set at January

[1] We compare this model with other ARIMA models with the form $POS_t^{2020} = \alpha + \beta POS_t^{2019} + \theta ARIMA + dummies + \varepsilon_t$ in terms of the root mean squared predicted error (RMSPE) for February 19 to March 11. This comparison is for total, credit, and debit expenditures, varying the introduction of dummies. For a complete table of the evaluated models see supplementary material Table S1. For simplicity, we choose the model with dummies to make the predictions.

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13, 2020. Apple also uses people's mobile devices to track their location (monitoring the requests made to the Apple map application). For Apple, we use the mobility measure based on driving. Data is available for the period January 13 to June 30.[2] For purposes of comparability between the Google and Apple datasets, we change the baseline to February 17. We thus obtain a dataset for the period February 15 to June 30, with each row including two columns: the percent change of total POS expenditure from state *s* in week *w*, and the mean percent change in mobility from each source from state *s* in week *w*. The percent change is with respect to February 17 in all columns.

$$\Delta\%POS_{s,w}^{2020} = \beta\Delta\%Mobility_{s,w}^{2020} + \delta_s + \delta_w + \varepsilon_{s,w} \qquad (3)$$

The regression controls for fixed effects of week and state. The first control is for shocks that affect all states at the same time, and the second is for permanent differences across states. For example, some states may specialize in occupations or industries that make them either more resilient or more susceptible to an economic shock, and this specialization may at the same time be correlated with geographic mobility.[3]

3. Descriptive Results

The first case of COVID-19 in Mexico was diagnosed on February 27, later than in European countries. On March 14, the government announced the suspension of non-essential activities and rescheduled mass events. A soft lockdown began on March 23. The government has taken different steps to address the health and economic shocks. First, it implemented recommendations for social distancing, travel restrictions, and the suspension of non-essential activities to prevent the spread of the virus. Second, the

[2] Two days, May 11 and May 12, were not available. We impute values for these days with the mean values for May 10 and May 13.

[3] In particular, some states may be more prepared for telecommuting than others, making them more resistant to employment losses. If the latter states show greater mobility and expenditure, that could bias the elasticity estimate.

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government and the Banco de México have taken action to mitigate the effects of the pandemic. Like other central banks across the world, the Banco de México has implemented measures to provide liquidity to the market, injecting the equivalent of 3.3 percent of GDP into the economy.[4] The fiscal policy response has been more limited: it has offered access to microcredits and has implemented a frontloaded payment of some social programs (close to 1 percent of GDP). The government has also announced an austerity program and the continuation of some public works.

Table 1 shows the main descriptive statistics for May 2019 and May 2020, including the total amount spent in POS terminals, the average amount of each transaction, and the share of expenditures in each group. For simplicity the data is grouped into 12 categories: tourism (travel agencies and hotels), education (universities, colleges, basic education, and daycare), health care (pharmacies, hospitals, physicians, and dentists), food services (restaurants and fast food), trade (wholesale and retail), transportation (air transportation, ground transportation, tolls, parking lots, and car rental), insurance, telecommunications, supermarkets, big-box stores, and others.

The average transaction amount did not change substantially. It was $601 in May 2019 and $589 in May 2020 (in constant MXN pesos of July 2018). However, there is an overall decline of approximately $34 billion, or 16 percent, representing an average monthly decline in total private consumption of 2.5 percent a month. The sectors with the largest expenditures in 2019 (a combined total of 80 percent) were big-box stores, trade, gasoline, food services, and other. In May 2020, most sectors showed reduced total POS transactions. Services related to tourism, food services, and transportation were hit

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[4] These measures have included bond swaps, loosened rules for minimum deposits from commercial banks, and facilities to swap assets with the central bank in order to obtain credit. These measures have the goal of directing credit to small and medium-sized business.

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especially hard. However, insurance, telecommunications, big-box stores, and other maintained or increased sales.

Table 1. Descriptive Statistics

	May 2019			May 2020		
	Total Amount (millions of pesos)	Avg. Transaction amount (pesos)	Share (%)	Total Amount (millions of pesos)	Avg. Transaction amount (pesos)	Share (%)
Total	$206,669	$ 601		$172,800	$589	
Tourism	$5,333	$ 2,580	2.6	$786	$1,988	0.5
Education	$6,851	$ 4,026	3.3	$4,607	$4,639	2.7
Health Care	$8,239	$ 524	4.0	$7,757	$485	4.5
Food Services	$11,747	$ 383	5.7	$2,681	$257	1.6
Trade	$42,312	$ 473	20.5	$32,978	$462	19.1
Transportation	$8,961	$ 589	4.3	$1,833	$286	1.1
Insurance	$5,153	$1,811	2.5	$5,445	$2,207	3.2
Telecomm. Services	$6,394	$ 701	3.1	$6,779	$525	3.9
Gasoline	$18,400	$616	8.9	$ 10,979	$538	6.4
Other	$35,244	$641	17.1	$ 41,564	$601	24.1
Supermarkets	$28	$348	0.0	$19	$314	0.0
Big-Box Stores	$58,007	$630	28.1	$57,373	$692	33.2

Notes: Authors' calculations. Amounts are in constant MXN for July 2018.

3.1 Aggregate Results

Figure 1 shows smoothed lines of daily expenditure in POS terminals for 2019 and 2020. For comparison purposes, the series are in relative terms with respect to January 14 of each year. The red line is the index for 2019 and the blue line for 2020. Using the method described above, we obtain a prediction for 2020 using data for the early part of the year. The green line is the prediction for 2020. Before the lockdown, the patterns for 2019 and 2020 are similar. When the lockdown starts, POS expenditures fall drastically. The worst days were in mid-April, with expenditures about 35 percent lower than in 2019

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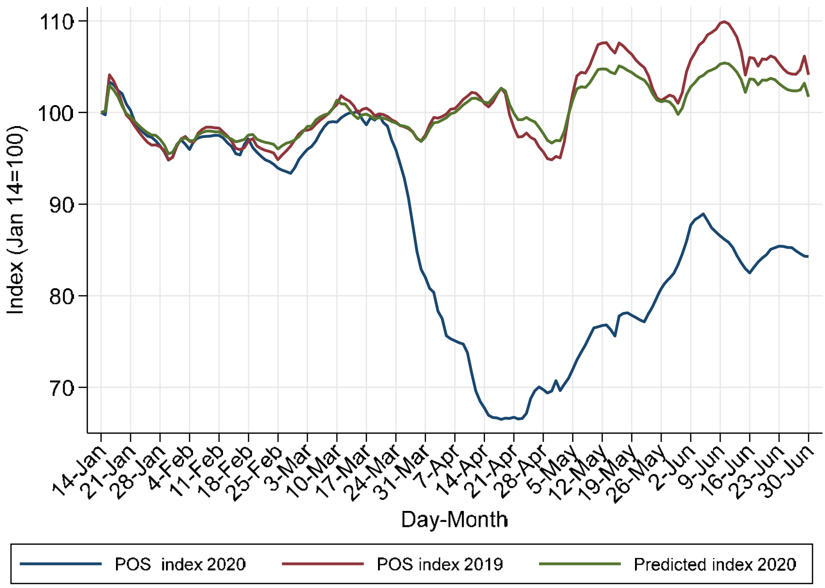
or in the prediction for 2020. After that point, expenditures slowly started to recover. By late May and early June, the shortfall was only about 15 percent lower than the prediction.

Figure 1. Effect of COVID-19 on expenditures in POS terminals



Notes: Authors' calculations. Lines are smoothed using a moving average for the previous two weeks. Predicted line is obtained with equation (3), an OLS of the amount in 2020 with the amount in 2019. Expenditures are in constant pesos (MXN) of July 2018. Expenditures in January 2020 are 9 percent larger than in January 2019.

Figure 2 shows the decline in POS expenditures by month (constant pesos of July 2018), with comparisons to 2019 and the predicted expenditures for 2020. The greatest decline is in April, with expenditures 30 percent lower than predicted and 23 percent lower than in the corresponding period in 2019. Subsequent months show lesser declines: May is 22 percent and June is 18 percent below the prediction. The total decline in POS expenditures from the predicted figure for April through June is around \$149 billion MXN, a loss of 3.9 percent of an average quarter of private consumption in 2019, and a loss of 2.6 percent of an average quarter of GDP.

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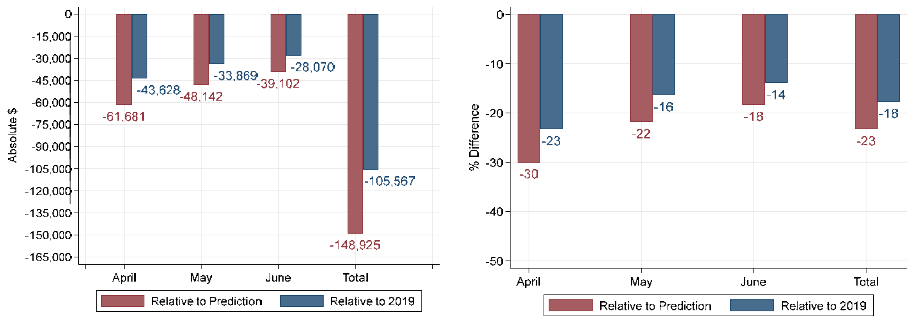
Figure 2. Decline in POS expenditures

A. Absolute decline **B. Percent decline**



Note: Authors' calculations. This graph shows the difference between actual and predicted values, and the difference between actual 2020 and 2019 values (in constant pesos of July 2018).

3.2 Results by Sector

Figure 3 shows the change in consumption patterns by sector. The lines are smoothed using a moving average of the previous two weeks (Leatherby and Gelles 2020), and the comparison is to the predicted sales in each sector. The comparison with respect to 2019 can be found in the Supplementary Materials. After the beginning of the lockdown, there is a sharp decline in education, tourism, food services, and transportation. Only education recovers, but at the end of May it is still about 40 percent below the prediction. Tourism, food services, and transportation fall from 80 to 90 percent by mid-April. Because of the decline in mobility and in domestic prices, POS expenditures for gasoline decrease almost 50 percent in mid-April, and by the end of May they were still approximately 35 percent below the prediction. Expenditures in June have been relatively stable, with a slight recovery in most cases.

Similar to the experience of other countries, POS expenditures in big-box stores increased in the last two weeks of March, an effect of panic buying to stockpile goods.

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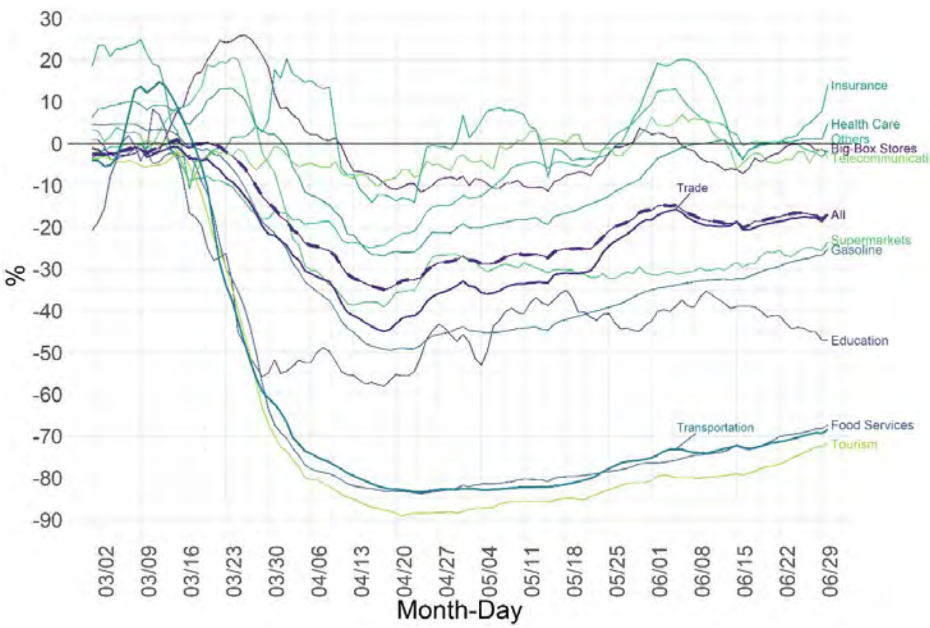
Other sectors, like insurance, health care, and telecommunications, were not affected by the mobility restrictions. At least with insurance and telecommunications, this is likely related to direct billing options as well as the inelasticity of demand for this type of goods. While in the U.S. there was a large decline in health expenditures in April (Chetty et al. 2020), in Mexico the decline was smaller and it quickly recovered, by the end of May.

Figure 3. Changes in consumption patterns by sector. Smoothed lines.



Notes: Authors' calculations. Comparison is to predicted sales in each sector. Constant pesos (MXN) of July 2018. Smoothed with moving average of the previous two weeks.

Figure 4 summarizes previous estimates. It indicates the percent difference of POS expenditures in 2020 with respect to the predicted expenditures and with respect to the same period in 2019 (in constant pesos). The losses total 23 percent of predicted expenditures: one quarter of expected POS sales did not take place. Total expenditures were 18 percent lower than in the same period in 2019. Comparisons are difficult because

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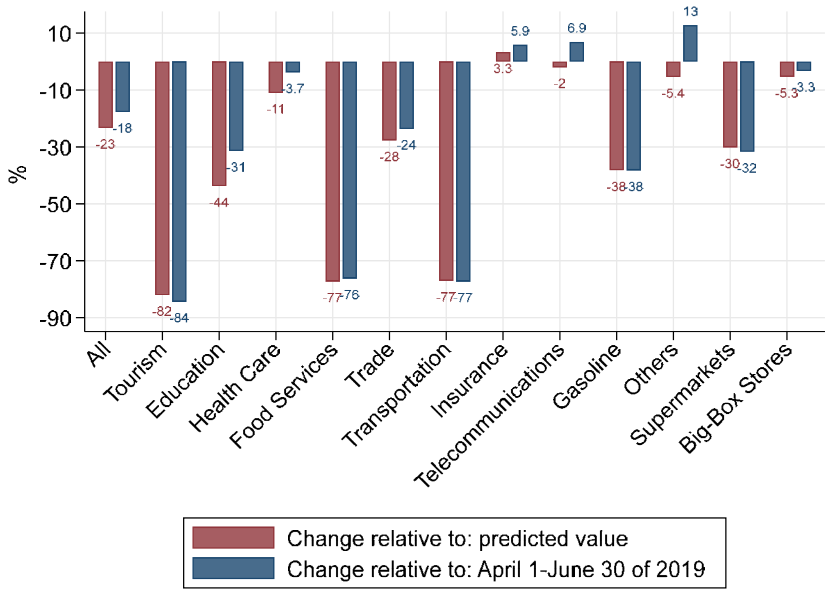
lockdowns were implemented at different times in different countries, but the Mexican loss estimate is among the lowest. In the last two weeks of March, France and Spain had expenditure losses of 50 percent (Bounie et al. 2020; Carvalho et al. 2020); in April, Portugal had losses of 55 percent (Carvalho, Peralta, and Pereira, 2020) and Denmark had more moderate losses of approximately 30 percent.

Figure 4. Summary of expenditure losses. April-June 2020.



Note: Authors' calculations. This graph shows the change in expenditures relative to 2019 values and to predicted values for 2020. Constant pesos (MXN) of July 2018.

The comparison with the U.S. depends on the source. The estimates of Baker et al. (2020) imply a decline of 50 percent, while Chetty et al. (2020) find a decline of 30 percent in the last two weeks of March. In fact, the change in All Expenditures in Figure 3 is very close to that found in Chetty et al. (2020) (see Figure S3 in Supplementary Materials). The decline in expenditures in the U.S. was larger before mid-April. Stimulus payments began on April 15 in the U.S., and POS expenditures recovered faster around

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that date. The decline in POS expenditures from January to mid-June was 10 percent in the U.S., while in Mexico it was still 20 percent. There is significant heterogeneity across sectors, however. Those affected most severely in Mexico were tourism, food services, and transportation, where expenditures declined approximately 80 percent. This is similar to what previous studies have found in Denmark, Spain, the United States, and other countries (Andersen et al. 2020a; Baker et al. 2020; Carvalho et al. 2020; Chetty et al. 2020; Leatherby and Gelles 2020).

Some sectors in Mexico even had gains or only small losses. Expenditures on insurance increased slightly in the period, and expenditures on telecommunications decreased slightly. We interpret these sectors as supplying highly inelastic necessities. Expenditures in big-box stores decreased by 5.4 percent. The pattern for these stores is mixed: in mid-March their expenditures increased, in mid-April they declined, and by the end of May they recovered. This group includes large supermarkets (such as Walmart and Soriana) as well as department stores (such as Liverpool, Palacio de Hierro, and Sears). It is likely that sales increased in large supermarkets and decreased in department stores.

There were decreased sales in health care, gasoline, trade, small supermarkets, and other, which accounted for close to 50 percent of all expenditures in 2019 (Table 1). The decline in trade and gasoline (28 and 38 percent, respectively) is directly related to restrictions in mobility.

3.3 Results by State

We estimate the model in equation (1) for each state in Mexico. Figure 5 shows percent losses by state with respect to the predictions of the model. States shown in purple are the hardest hit and those in yellow are the least affected. The hardest hit regions depend on international tourism: Quintana Roo and Yucatan in the south, as well as

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Guerrero and Nayarit. These states lost all expected revenue from the spring vacation season. Other states closer to Mexico City are also greatly affected: Michoacán, Estado de México, Puebla, and Morelos, probably related to the loss of domestic tourism around Easter. Mexico City is not as affected as other states. We suspect that here the effects of the pandemic were partially compensated by online sales, but our data unfortunately does not distinguish online from other sales. Finally, states in the north are not as affected as the rest, an effect of greater mobility than in the rest of Mexico, as explained in the next section.

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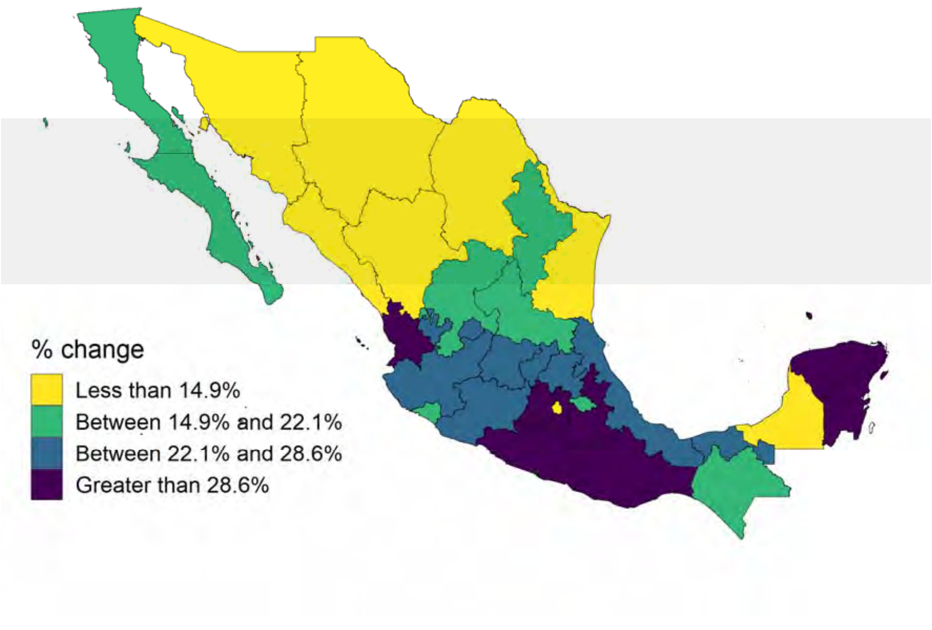
Figure 5. Losses by state in total POS expenditure (percent).



Notes: Authors' calculation. The map shows the percent change of POS expenditures from April to June with respect to the predicted sales for each state. Constant pesos of July 2018

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4. Consumption and Mobility

We use geographic mobility data from Google (2020) and Apple (2020) through June 2020. There is an ongoing debate about the relationship between mobility and POS expenditures. The case and evidence from Sweden are relevant.[5] Unlike other European countries, Sweden did not impose a lockdown in response to the COVID-19 pandemic, which was responsible for a higher mortality rate than in similar Nordic countries. One might expect that the lack of restrictions on mobility at least lessened the economic effects of the pandemic. However, Andersen et al. (2020b) found that this was not the case. Sweden experienced a 25 percent reduction in POS expenditures from March 11 to April 12; the corresponding figure for Denmark was 29 percent. Apple's measure of driving mobility for early April shows a reduction in Sweden of 12 percent and a reduction in Denmark of 32.4 percent. The between-country variation suggests that the elasticity of mobility is around 0.20. However, elasticity may depend on the relative importance of internet sales, which depends in turn on the depth of the financial sector. In a less developed country like Mexico, in-person sales and therefore mobility may matter much more than in developed economies.

To show how mobility and expenditures are related, we use Google's measure of workplace mobility and Apple's measure of driving mobility. We calculate mobility and expenditure patterns for each of the 20 weeks and 32 states under study. We thus have a panel dataset with 640 observations. The patterns are shown in Figure 6. The variation in the mobility measures is positively correlated with the variation in the total amount spent. Panel A uses Google's workplace mobility and it finds a coefficient of 0.7 using a simple OLS regression. Panel B uses Apple's driving mobility and it finds a coefficient of 0.9

[5] https://www.politico.eu/article/swedens-cant-escape-economic-hit-with-covid-19-light-touch/, https://www.ft.com/content/93105160-dcb4-4721-9e58-a7b262cd4b6e.

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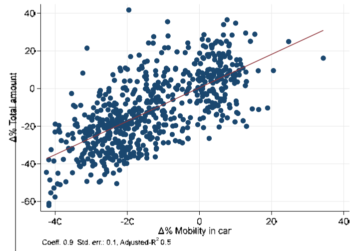
with the same type of regression. States with the largest declines in mobility are related to the largest declines in expenditures at the weekly level.

Figure 6. Relationship between mobility (Google and Apple) and POS expenditures.

A. Google: Workplace Mobility

B. Apple: Driving Mobility



Notes: Authors' calculations. Each dot is the percent change of mobility or POS expenditures (constant pesos of July 2018) in week *w* with respect to February 17 for each of the 32 states in Mexico. Period of estimation is February 15 to June 30.

In order to analyze this claim more carefully, we estimate different versions of equation (3). Panel A in Table 2 estimates the relationship between changes in POS expenditures and mobility in Mexico including week and state fixed effects. These effects control for permanent differences across states (for example, density or geographic characteristics) as well as for temporal shocks that affect all states at the same time. Table 2 shows the results for all expenditures as well as for expenditures differentiated by credit versus debit card. The elasticity coefficient for total expenditure using Google's mobility is 0.73; for Apple's mobility it is 0.93. These estimates, which exploit the within-state variation, are very similar to those obtained simply by pooling the spending and mobility information (Figure 6). All of the estimates in Panel A are very precisely estimated and they are all statistically significant. The elasticity using Apple's mobility information is not statistically different from 1. The elasticity for credit card spending is greater than for debit cards, regardless of the mobility indicator used.

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Panel B in Table 2 estimates the same spending-mobility relationship but instead of including fixed effects, it includes as an additional control variable the proportion of work that can be performed by telecommuting from home in each Mexican state, as estimated by Monroy-Gómez-Franco (2020). This specification exploits both the between and the within variation across states in Mexico to estimate the elasticity of POS expenditures with respect to mobility. The elasticity results obtained with this specification have larger standard errors, but they are similar for both mobility indicators (0.91). In both cases, they are statistically different from 0 but not from 1. As before, credit cards are more elastic with respect to mobility than debit cards. These estimated elasticities are also much larger than that implied by Andersen et al. (2020b) for the case of Sweden (0.2).

Table 2. Elasticity Estimates: Change in % POS Expenditures with Respect to Change in % Mobility

	Google: Workplace Mobility			Apple: Driving Mobility		
	Total	Credit	Debit	Total	Credit	Debit
A. Including state fixed effects						
Coefficient	0.73	1.09	0.56	0.93	1.33	0.74
Standard Error	[0.05]	[0.05]	[0.04]	[0.06]	[0.07]	[0.05]
R^2	0.45	0.54	0.35	0.46	0.44	0.41
Total Obs.	640	640	640	640	640	640
B. Controlling for telecommuting (without state fixed effects)						
Coefficient	0.91	1.34	0.67	0.91	1.03	0.85
Standard Error	[0.45]	[0.51]	[0.42]	[0.20]	[0.29]	[0.18]
R^2	0.57	0.63	0.51	0.65	0.66	0.62
Total Obs.	640	640	640	640	640	640

Notes: Authors' calculations. The dependent variable is the percent change in POS expenditures in week *w* with respect to February 17 for each state in Mexico, and the independent variable is the percent change in mobility for the same period. The regression in Panel A includes fixed effects for state and week. Estimation period is February 15 to June 27. Panel B includes dummies for weeks and proportion of telecommuting (defined as in Monroy-Gómez-Franco 2020). Standard errors clustered at the state level in brackets.

To further analyze these results, in Figure 7 we show Apple's mobility measure (blue line) and POS expenditures (red line) in high- and low-mobility states in Mexico.

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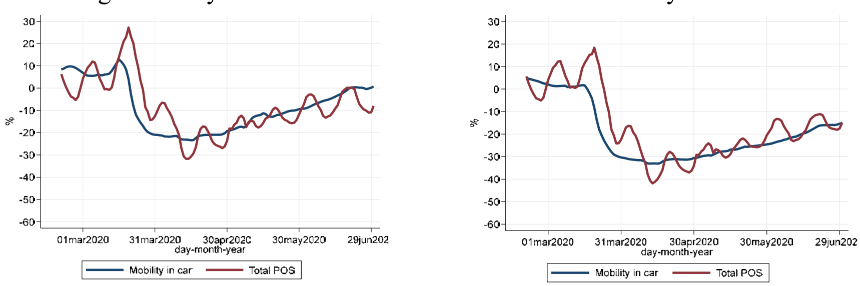
In high-mobility states, mobility and POS expenditures declined close to 10 percent from early in the year to the end of May. By mid-June, mobility and expenditures in these states were similar to pre-pandemic levels. In low-mobility states the decline was close to 25 percent in mid-May and by mid-June it was still around 15 percent below pre-pandemic levels. The high correlation between spending and mobility in both types of states is evident. As expected, the estimates of the elasticity of spending with respect to mobility are also very high for each of these groups of states: around 0.80 for high-mobility states and 1.04 for low-mobility states, and in both groups the elasticity for credit cards is larger than for debit cards. These elasticity estimates are between four and five times the implied elasticity estimated by Andersen et al. (2020b).

Figure 7. Apple's mobility and POS expenditures in high- versus low-mobility states.

A. High mobility

B. Low mobility.



Notes: Authors' calculations. High-mobility states include Aguascalientes, Campeche, Chihuahua, Coahuila, Colima, Durango, Guerrero, Michoacán, Morelos, San Luis Potosí, Sinaloa, Sonora, Tamaulipas, Tlaxcala, Veracruz, and Zacatecas. Low-mobility states include Baja California, Baja California Sur, Chiapas, Mexico City, Estado de México, Guanajuato, Hidalgo, Jalisco, Nayarit, Nuevo León, Oaxaca, Puebla, Querétaro, Quintana Roo, Tabasco, and Yucatán. Mobility refers to driving mobility measured by Apple.

Why is the elasticity of POS expenditures to mobility larger in Mexico? We conjecture that this difference is driven mainly by the strength (or lack thereof) of e-commerce, financial inclusion, and internet penetration. As mentioned in the introduction,

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financial inclusion is lower in Mexico than in China, the United States, and European countries. In 2014, the proportion of individuals in Mexico with an account at a financial institution was 40 percent, while it is 80 percent in China and close to 100 percent in developed countries. If we consider that internet penetration is lower as well, then we have a weaker market for e-commerce in Mexico than elsewhere. Indeed, results from the United Nations Conference on Trade and Development (2016) show that Mexico has an e-commerce readiness index much lower than other countries (Mexico's index is 49.1 while the U.S.'s is 82.6). POS transactions thus depend much more on mobility in Mexico than in other countries.

Finally, we cannot test Chetty's et al. (2020) claim that the channels of the decline in POS expenditures are mainly rich individuals in fear of contagion. We attempt to compare our results, at least at the aggregate level, by computing POS expenditures by credit versus debit cards, which are highly segregated in Mexico. We calculate that approximately 77 percent of credit cards and 62 percent of debit cards are held by individuals in the top 30 percent of the wealth distribution (see figures in Supplementary Materials). The decline in POS expenditures is larger for credit cards (28.6 percent) than for debit cards (10 percent). The elasticity of POS expenditures with respect to mobility is also much larger for credit cards than for debit cards. We thus conjecture that the decline in POS expenditures is partially driven by richer individuals concerned for their health, as in Chetty et al. (2020).

5. Summary

This paper analyzes consumption patterns in Mexico using the universe of POS transactions for the period from January 2019 to June 2020. Unlike some other countries, Mexico implemented a soft lockdown as well as a moderate countercyclical fiscal policy.

We find that POS expenditures for the April-June quarter are 23 percent less than they would have been in the absence of the pandemic. This difference is less than that calculated for European countries using similar data, and comparable to that reported for the U.S. by Chetty et al. (2020), also using results based on live POS data.

The losses we find for Mexico are heterogeneous across economic sectors and region. As in other studies, the more severely affected sectors are those related to tourism (travel agencies and hotels), food services (such as restaurants), and transportation. States that benefit more directly from tourism (beach resorts and other tourist destinations) were also more affected.

There is a debate about whether mobility patterns affect POS expenditures and thus economic activity. We find that the elasticity of POS expenditures with respect to mobility is close to 1 (0.93 using Apple's measure of mobility in one specification and 0.91 for both Google's and Apple's measures of mobility in another). These estimates are much larger than the implied elasticity estimated by Andersen et al. (2020b) for Sweden. Our estimate likely indicates that POS expenditures in developing countries with shallower financial sectors are more responsive to mobility patterns than developed countries. It also suggests that mobility indicators, which can be observed almost in real time, could serve as a good proxy for the behavior of expenditures in some economies.

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References

Andersen, Asger, Emil Toft Hansen, Niels Johannesen and Adam Sheridan (2020a). "Consumer Responses to the COVID-19 Crisis: Evidence from Bank Account Transaction Data". *Centre for Economic Policy Research.* http://www.cepr.org/active/publications/discussion_papers/dp.php?dpno=14809

Andersen, Asger, Emil Toft Hansen, Niels Johannesen, and Adam Sheridan (2020b). "Pandemic, Shutdown and Consumer Spending: Lessons from Scandinavian Policy Responses to COVID-19". Working Paper arXiv:2005.04630v1.

Apple Inc. (2020). "Apple Mobility Trends reports". https://www.apple.com/covid19/mobility/ (Accessed: June 5th, 2020)

Baker, Scott R., R.A. Farrokhnia, Steffen Meyer, Michaela Pagel and Constantine Yannelis (2020). "How Does Household Spending Respond to an Epidemic? Consumption During the 2020 COVID-19 Pandemic". *Covid Economics* 18, 15 May 2020: 73-108.

Bounie, David, Youssouf Camara and John W. Galbraith (2020). "Consumers' Mobility, Expenditure and Online-Offline Substitution Response to COVID-19: Evidence from French Transaction Data". CIRANO Working Papers 2020-28.

Carvalho, Bruno P., Susana Peralta and Joao Pereira (2020). "What and How did People Buy during the Great Lockdown? Evidence from Electronic Payments". *Covid Economics* 28, 12 June 2020: 119-158.

Carvalho, Vasco, M., Stephen Hansen, Álvaro Ortiz, Juan Ramón García, Tomasa Rodrigo, Sevi Rodríguez Mora, and José Ruiz (2020). "Tracking the COVID-19 Crisis with High-Resolution Transaction Data". *Centre for Economic Policy Research.* https://cepr.org/active/publications/discussion_papers/dp.php?dpno=14642

Covid Economics 38, 16 July 2020: 218-252

Chen, Haiqiang, Wenlan Qian and Qiang Wen (2020). “The Impact of the COVID-19 Pandemic on Consumption: Learning from High Frequency Transaction Data”. *SSRN*. http://dx.doi.org/10.2139/ssrn.3568574

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and the Opportunity Insights Team (2020). **“**How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data.” National Bureau of Economic Research, NBER Working Paper 27431, https://doi.org/10.3386/w27431.

Google LLC. (2020). "Google COVID-19 Community Mobility Reports". https://www.google.com/covid19/mobility/ (Accessed: June 5th, 2020)

Guerrieri, Veronica, Guido Lorenzoni, Ludwig Straub, and Ivan Werning (2020). “Macroeconomic implications of COVID-19: Can negative supply shocks cause demand shortages?” National Bureau of Economic Research, NBER Working Paper 26918, https://doi.org/10.3386/w26918.

Hacioglu, Sinem, Diego Känzig and Paolo Surico (2020). "Consumption in the time of Covid 19: Evidence from UK transaction data". Centre for Economic Policy Research, CEPR Discussion Paper 14733. http://www.cepr.org/active/publications/discussion_papers/dp.php?dpno=14733

Instituto Nacional de Estadística y Geografía. (2018). “Encuesta Nacional de Inclusión Financiera (ENIF) 2018”. https://www.inegi.org.mx/programas/enif/2018/ (Accessed: June 5th, 2020)

Kahn, Lisa B., Fabian Lange, and David G. Wiczer (2020). “Labor Demand in the Time of COVID-19: Evidence from Vacancy Postings and UI Claims.” National Bureau of Economic Research, NBER Working Paper 27061, https://doi.org/10.1017/CBO9781107415324.004.

Covid Economics 38, 16 July 2020: 218-252

Lewis, Daniel, Karel Mertens, and James H. Stock (2020). "US economic activity during the early weeks of the SARS-Cov-2 outbreak". National Bureau of Economic Research, NBER Working Paper 26954, https://doi.org/10.3386/w26954

Leatherby, Lauren and David Gelles (2020). "How the Virus Transformed the Way Americans Spend Their Money" *New York Times*. April 11. https://www.nytimes.com/interactive/2020/04/11/business/economy/coronavirus-us-economy-spending.html?referringSource=articleShare

Monroy-Gómez-Franco, Luis (2020). "¿Quién puede trabajar desde casa? Evidencia desde México.", Documento de Trabajo no. 06/2020. Centro de Estudios Espinosa Yglesias. https://ceey.org.mx/wp-content/uploads/2020/05/06-Monroy-G%C3%B3mez-Franco-2020.pdf

United Nations Conference on Trade and Development (2016). *UNCTAD B2B E-Commerce Index 2016* (Vol. 7). https://unctad.org/en/PublicationsLibrary/tn_unctad_ict4d07_en.pdf

World Bank (2020). Data indicators. Data.worldbank.org. Series: https://data.worldbank.org/indicator/FD.AST.PRVT.GD.ZS?locations=US-ES-GB-CN-DK-FR&name_desc=true,

https://databank.worldbank.org/reports.aspx?source=1251&series=GPSS_4

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Supplementary Materials

Table S1. RMSPE Tested Models

		RMPSE February 19-March 11		
Model #	**Model description**	**Total**	**Credit**	**Debit**
1	OLS	547.83	267.93	414.86
2	OLS dummies	425.40	197.64	299.30
3	ARIMA(0, 0 ,0)	547.83	267.93	414.86
4	ARIMA(0, 1 ,0)	598.36	268.81	479.59
5	ARIMA(0, 2 ,0)	6153.22	2450.88	1082.39
6	ARIMA(0, 0 ,1)	551.20	259.99	413.24
7	ARIMA(0, 1 ,1)	538.81	281.95	396.49
8	ARIMA(0, 2 ,1)	695.04	450.37	434.59
9	ARIMA(0, 0 ,2)	559.96	278.89	420.63
10	ARIMA(0, 1 ,2)	544.82	271.71	391.56
11	ARIMA(0, 2 ,2)	549.44	277.89	412.70
12	ARIMA(1, 0 ,0)	547.46	267.40	413.63
13	ARIMA(1, 1 ,0)	519.04	296.20	455.55
14	ARIMA(1, 2 ,0)	2892.21	645.85	817.03
15	ARIMA(1, 0 ,1)	561.43	282.26	414.88
16	ARIMA(1, 1 ,1)	539.55	280.94	394.15
17	ARIMA(1, 2 ,1)	586.35	386.94	451.30
18	ARIMA(1, 0 ,2)	556.11	276.08	418.16
19	ARIMA(1, 1 ,2)	531.36	272.46	394.61
20	ARIMA(1, 2 ,2)	548.14	276.24	433.78
21	ARIMA(2, 0 ,0)	543.16	276.84	420.12
22	ARIMA(2, 1 ,0)	509.93	253.88	440.78
23	ARIMA(2, 2 ,0)	1937.40	963.75	2354.00
24	ARIMA(2, 0 ,1)	545.08	265.54	419.62
25	ARIMA(2, 1 ,1)	537.28	285.54	403.67
26	ARIMA(2, 2 ,1)	512.18	246.57	436.00
27	ARIMA(2, 0 ,2)	436.47	277.93	422.59
28	ARIMA(2, 1 ,2)	536.05	273.96	399.86
29	ARIMA(2, 2 ,2)	548.95	288.44	424.83
30	ARIMA(0, 0 ,0) dummies	425.40	197.64	299.30
31	ARIMA(0, 1 ,0) dummies	476.93	225.70	276.60
32	ARIMA(0, 2 ,0) dummies	7886.29	2126.09	1792.76
33	ARIMA(0, 0 ,1) dummies	456.05	218.66	296.66
34	ARIMA(0, 1 ,1) dummies	415.38	202.44	284.85
35	ARIMA(0, 2 ,1) dummies	798.20	557.02	318.68
36	ARIMA(0, 0 ,2) dummies	477.72	241.28	306.00
37	ARIMA(0, 1 ,2) dummies	425.18	219.22	282.93
38	ARIMA(0, 2 ,2) dummies	405.73	650.48	339.80
39	ARIMA(1, 0 ,0) dummies	425.47	196.96	297.46
40	ARIMA(1, 1 ,0) dummies	417.76	225.53	257.01
41	ARIMA(1, 2 ,0) dummies	4905.65	980.97	2054.57
42	ARIMA(1, 0 ,1) dummies	469.24	212.66	310.32
43	ARIMA(1, 1 ,1) dummies	415.31	199.39	283.38
44	ARIMA(1, 2 ,1) dummies	719.47	593.73	298.22
45	ARIMA(1, 0 ,2) dummies	476.83	211.87	308.88
46	ARIMA(1, 1 ,2) dummies	429.18	214.44	286.64
47	ARIMA(1, 2 ,2) dummies	714.69	611.71	265.89
48	ARIMA(2, 0 ,0) dummies	438.86	269.24	303.32
49	ARIMA(2, 1 ,0) dummies	456.70	248.57	259.42

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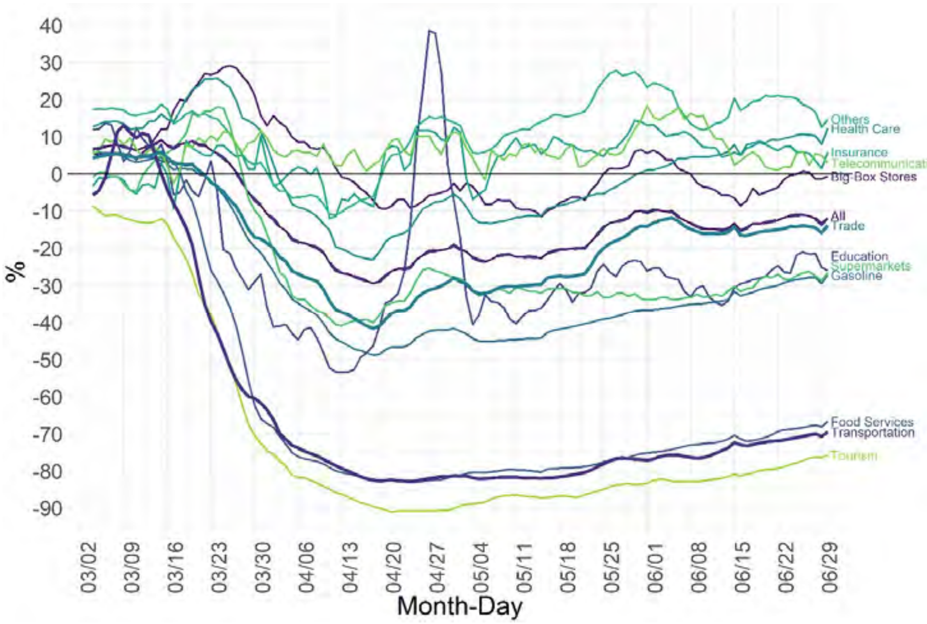
50	ARIMA(2, 2 ,0) dummies	827.67	1036.05	1455.96
51	ARIMA(2, 0 ,1) dummies	455.71	265.13	313.65
52	ARIMA(2, 1 ,1) dummies	420.19	251.79	288.18
53	ARIMA(2, 2 ,1) dummies	438.43	250.41	279.31
54	ARIMA(2, 0 ,2) dummies	No convergence	260.20	311.00
55	ARIMA(2, 1 ,2) dummies	415.41	268.92	288.83
56	ARIMA(2, 2 ,2) dummies	381.85	278.92	270.50

Notes: Models estimated for first 7 weeks of 2020. All the models are controlled for the amount in the corresponding weeks of 2019. Dummies refers to paydays, Mondays, Fridays, and December. RMPSE calculated for February 19 to March 11.

Figure S1. Changes in consumption patterns by sector with respect to corresponding period in 2019.



Notes: Authors' calculations. Comparison is to corresponding period in 2019 (in constant pesos of July 2018).

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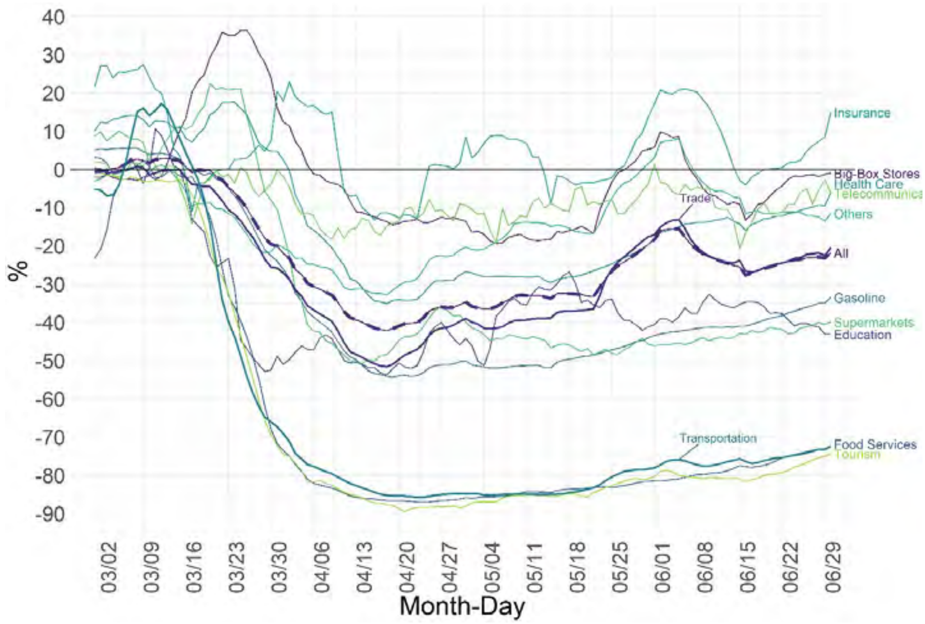
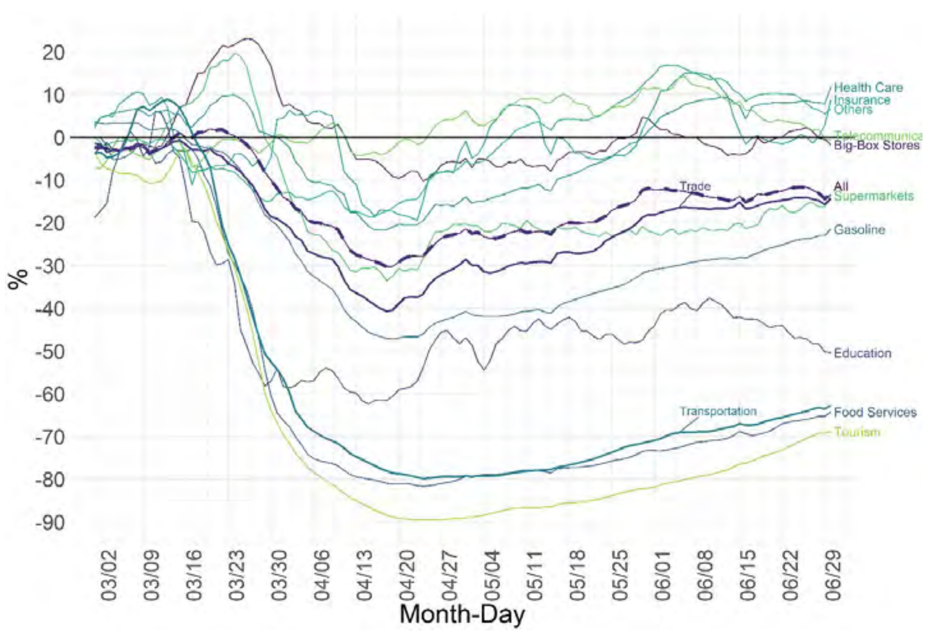
Figure S2. Changes in consumption patterns by sector with respect to corresponding period in 2019.

A. Credit cards

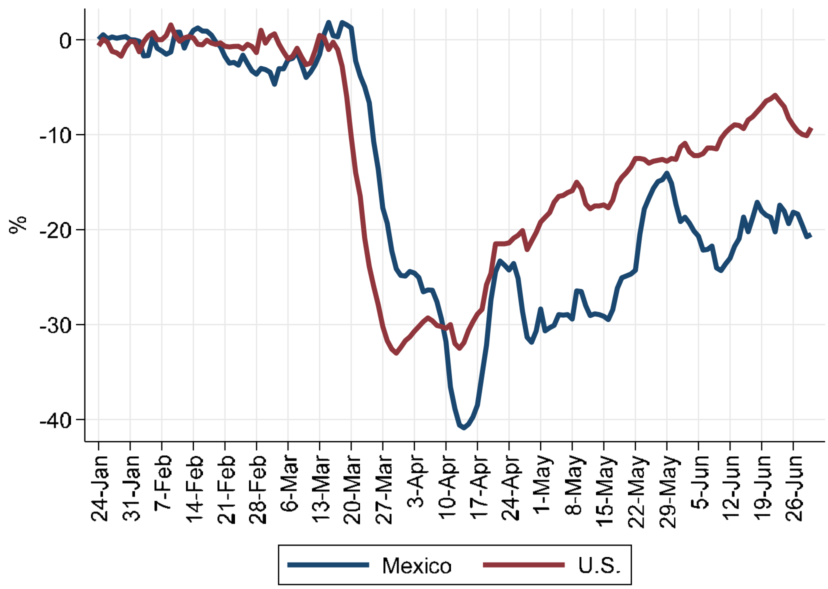


B. Debit cards



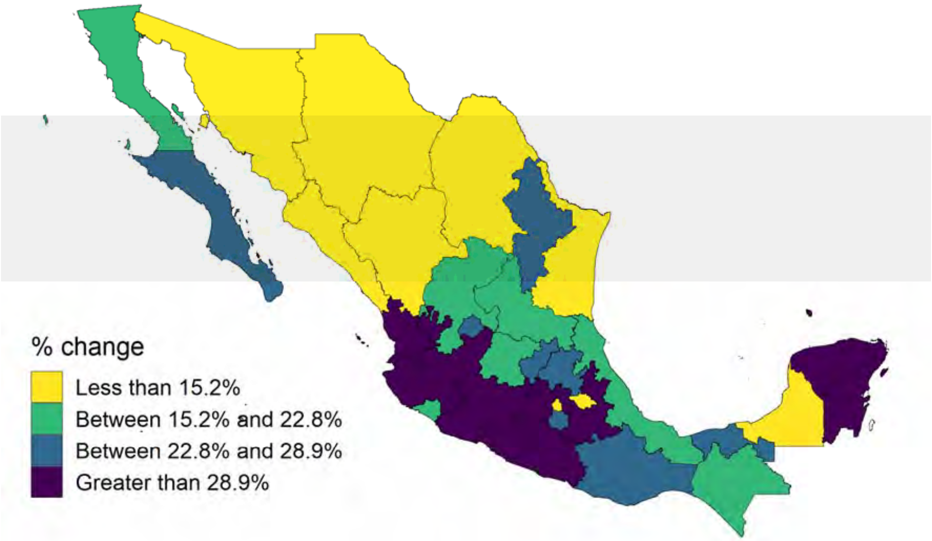
Notes: Authors' calculations. Comparison is to corresponding period in 2019 (in constant pesos of July 2018).

Figure S3. Comparison of expenditures in Mexico and U.S. Smoothed lines.



Note: Authors' calculations for the Mexican series. For the U.S., we used the calculation published by Chetty et al. (2020) and the https://tracktherecovery.org/ webpage. Both series use exactly the same construction. We first take a seven-day moving average, then we divide the 2020 series by the 2019 calendar day-month values. Finally, we divide the series by its average value for January 4-31.

Figure S4. Losses by state in total POS expenditure.



Notes: Authors' calculation. The map shows the percent change in POS expenditures from April to June with respect to sales for each state in the same period in 2019. Constant pesos of July 2018.

Table S3. Elasticity Estimates: Change in Percent Sales with Respect to Change in Percent Mobility, Panel by Day

	Google: Workplace Mobility			Apple: Driving Mobility		
	Total	Credit	Debit	Total	Credit	Debit
Coefficient	0.59	0.83	0.49	0.84	1.17	0.68
Standard Error	[0.04]	[0.05]	[0.03]	[0.05]	[0.08]	[0.04]
R^2	0.27	0.31	0.21	0.31	0.32	0.26
Total Obs.	4384	4384	4384	4384	4384	4384

Notes: Authors' calculations. The dependent variable is the percent change in POS expenditures on day *d* with respect to February 17 for each state in Mexico; the independent variable is the percent change in mobility. The regression includes fixed effects for state and day. The estimation period is February 15 to June 30. Clustered standard errors at state level.

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Table S4. Elasticity estimates: Change in % POS expenditures with respect to change in % Mobility

	Apple: High Driving Mobility			Apple: Low Driving Mobility		
	Total	Credit	Debit	Total	Credit	Debit
Coefficient	0.80	1.21	0.63	1.04	1.43	0.83
Standard Error	[0.05]	[0.08]	[0.04]	[0.09]	[0.11]	[0.07]
R^2	0.31	0.35	0.24	0.57	0.56	0.52
Total Obs.	320	320	320	320	320	320

Notes: Authors' calculations. The dependent variable is the percent change in POS expenditures in week *w* with respect to February 17 for each state in Mexico; the independent variable is the percent change in mobility for the same period. The regression includes fixed effects for state and week. Estimation period is February 15 to June 27. Clustered standard errors at the state level in brackets. High mobility states include Aguascalientes, Campeche, Chiapas, Chihuahua, Coahuila, Colima, Durango, Michoacán, Morelos, San Luis Potosi, Sinaloa, Sonora, Tamaulipas, Tlaxcala, Veracruz, and Zacatecas; low mobility states include Baja California, Baja California Sur, Mexico City, Estado de México, Guanajuato, Guerrero, Hidalgo, Jalisco, Nayarit, Nuevo León, Oaxaca, Puebla, Querétaro, Quintana Roo, Tabasco, and Yucatán. High mobility refers to driving mobility measured by Apple.

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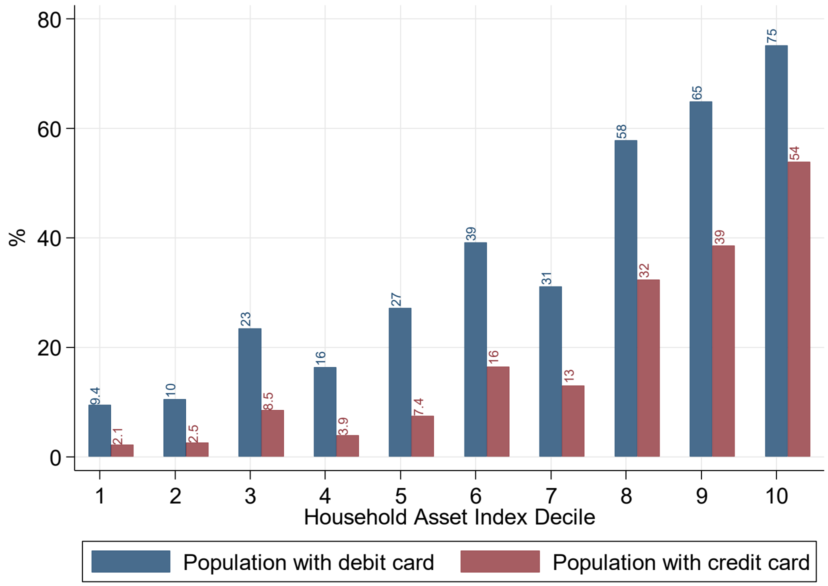
Figure S5. Cardholding by household asset index decile



Notes: Authors' calculation with data from the INEGI intergenerational social mobility module (2016). Household asset index was constructed with PCA of the covariance matrix using asset holding (television, vehicles, home ownership, telephone, internet access, radio, DVD, blender, toaster, microwave, refrigerator, stove, washing machine, iron, sewing machine, fan, tablet computer, videogame console, computer, printer, and livestock) and years of schooling.

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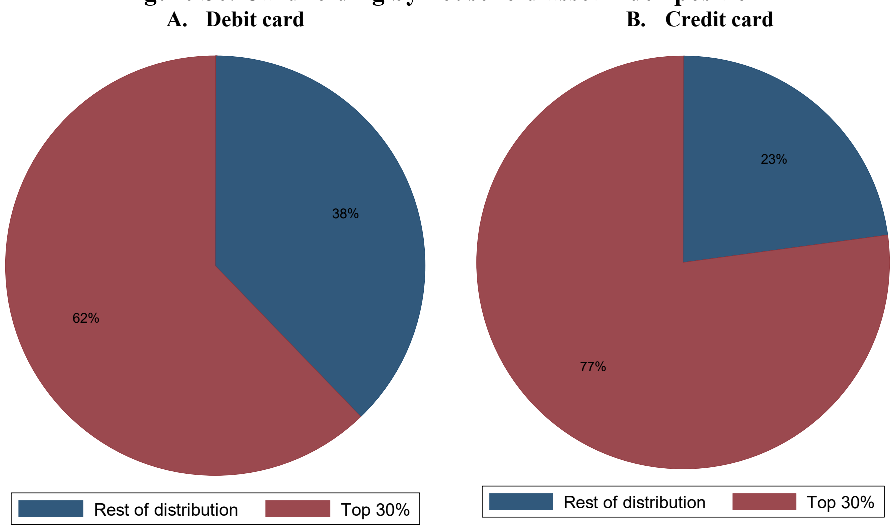
Figure S6. Cardholding by household asset index position



Notes: Authors' calculation with data from INEGI intergenerational social mobility module (2016). The graph shows the percent of credit (debit) cardholding by household asset index distribution. Household asset index was constructed with PCA of the covariance matrix using asset holding (television, vehicles, home ownership, telephone, internet access, radio, DVD, blender, toaster, microwave, refrigerator, stove, washing machine, iron, sewing machine, fan, tablet computer, videogame console, computer, printer, and livestock) and years of schooling.

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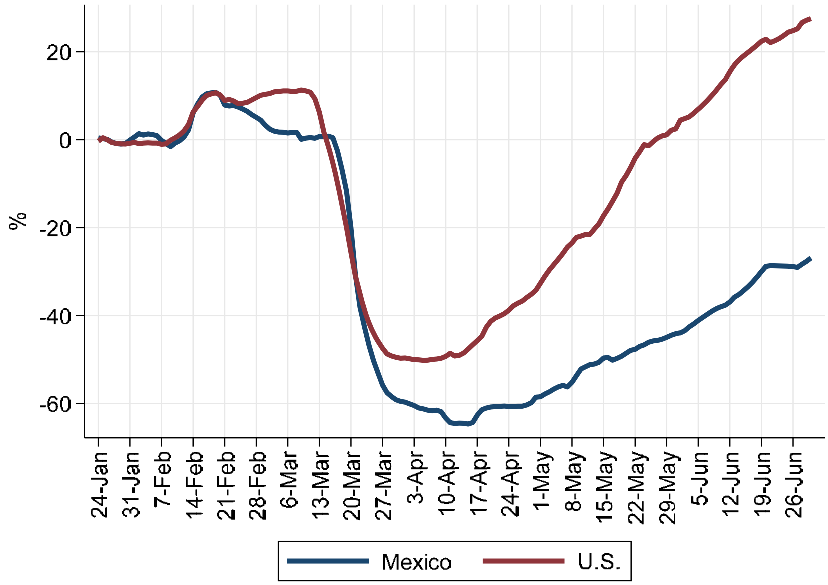
Figure S7. Comparison of mobility between United States and Mexico



Notes: Authors' calculation. Mobility uses Apple (2020) driving mobility. Base index is January 2020.

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