

An offer that you can't refuse?  
Agrimafias and Migrant Labor on Vineyards  
in Southern Italy

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**Abstract**

*Caporalato* is a widespread system of illegal recruitment and exploitation of underpaid farm labor run by Italian agrimafias. Most of this labor consists of irregular migrants vulnerable to exploitation due to their illegal status and the need of documents. In the 2011 migration wave over 64,000 migrants illegally landed on southern Italian coasts, and many of them may have supplied illegal workforce to farms through caporalato. To test this hypothesis, we evaluate the causal effects of the 2011 migration wave on measured labor productivity and reported wages focusing on vineyards in southern Italy. Our results show a significant increase of labor productivity by about 14% on average for 2011/2012, while average hourly wages are 7.3% to 23.8% lower than those predicted. This points towards the unreported employment of illegal workforce which competes with as well as partly substitutes and/or complements legal labor.

**Keywords:** Migration wave, Agrimafia, Vineyard productivity, Synthetic control  
**JEL Codes:** F22, J61, J43

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# 1 Introduction

In 2011, in the aftermath of the Arab Spring uprisings and the escalating Syrian civil war, the largest migration wave of the last decades crossed the central Mediterranean, and over 64,000 migrants landed in Apulia, Calabria and, primarily, Sicily (FRONTEX, 2016). After disembarking, migrants usually want to continue onwards to other EU countries like Germany and Sweden (Kirgegaard, 2016). However, any undocumented migrant landing on Italian coasts is illegal (Italian Penal Code, 2009) and at risk of expulsion. Relying on the promise to obtain (forged) documents and journey facilitations, migrants enter *caporalato*, an increasingly widespread system run by agrimafias which recruit and exploit underpaid workforce (Flai-Cgil, 2016).<sup>1</sup> However, although up to 500,000 immigrants are estimated to be irregularly employed as crop farm workers in Italy (Flai-Cgil, 2014), there is little empirical evidence on the impact of migration waves on agricultural labor markets, in particular with respect to the European Union (EU).<sup>2</sup>

For the first time, this study investigates potential illegal employment of migrant labor in farmlands of southern Italy after the 2011 migration wave. This large and unexpected migrant inflow characterizes a quasi-experimental setting (Dustmann et al., 2016; Peri, 2016), and we use this exogenous variation to estimate causal effects on labor productivity and wages in the winegrowing business. We assume that illegal employment would lead to overreported labor productivity and may impact wages of legal employment. We focus on the southern regions Sicily and Apulia, which are the recipients of the migrant wave (FRONTEX, 2016) and among Italy's market leaders in terms of wine and grape production.

Focusing on the wine and grape sectors in Sicily and Apulia is particularly meaningful as the competitive pressure on the Italian and southern European markets increased due to several factors: (I) The strong rise of international wine production between 2000 and 2010, and the arrival of non-EU wines, (II) a worldwide shrinking wine demand and a credit freeze following the 2008 economic crisis, (III) climatic shocks in 2003 and 2007, and (IV) failed agricultural policies leading to deregulation of the EU winegrowing sector with the liberalization of planting rights (CMO, 2008).

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<sup>1</sup>The first law recognizing and punishing *caporalato* entered into force in November 2016 (Italian Penal Code, 2016).

<sup>2</sup>The estimated value of agrimafias' illegal business in Italy ranges from 14 to 17.5 billion euros, profits obtained from the trade of crops and refined products like tomatoes, grapes, wine, and animal-derived products. Of the 10,311 firms sequestered or confiscated in Italy from 1982 to 2016, about 50% are farmlands, and 75% were detected only since 2011 (Flai-Cgil, 2016).

Worsening the market position of the EU producers, these developments demanded new strategies to cut costs and increase international competitiveness, in particular for the (small) less favored vine-growing areas at risk of further depression and possible abandonment also due to the excessive industrialization of growing methods (Gaeta and Corsinovi, 2014). In parallel, Italian agrimafias supply underpaid illegal workforce to farmers, e.g., for grape harvesting, which may allow farmers to reduce factor prices and to sustain the increasing global competition. This, however, comes at the cost of illegal migrant workers who lack any legal protection, cannot leave the illegal framework, and are heavily exploited (Flai-Cgil, 2016).

Therefore, labor market effects in the winegrowing sector are expected in response to both agrimafias' activity and immigrants with high incentives to enter illegal labor channels to obtain documents and/or journey facilitations. For this reason, labor market adjustments are likely to occur in the very short-term, when no reaction of other economic factors is expected. Furthermore, the 2011 migration wave, hereafter also called treatment, is an exogenous shock: It was unexpected and abnormally large, and hit the southern Italian coasts only due to its geographic vicinity as a consequence of the conflicts and poverty in the country of origin. Thus, the treatment assignment can be considered as good as random, which ensures independence between the treatment and potential outcomes, i.e., non-migrants do not affect migrant employment in vineyards. In addition, other political and economic dynamics of the immigrants' countries of origin do not affect southern Italy as these economies are not interconnected, and no spillovers occur. Lastly, no treatment effect is expected outside Sicily and Apulia because both agrimafias and a sudden migrant inflow are simultaneously present only there.

To perform counterfactual analysis, we use aggregated farm-level data at regional level for Italy and France between 1991 and 2012. We assign Sicily and Apulia to the treatment group, both separately and as a weighted average (called the *Treated South*). We assume that the employment of illegal labor increases productivity measures because illegal labor is not reported. Three major transmission channels affecting productivity and wages are possible: First, illegal labor can be employed to replace legal labor and/or capital inputs. Such a "displacement effect" results in an increase in measured labor productivity under the assumption that illegal labor can substitute homogeneous unskilled labor without sacrificing learning effects. Second, illegal labor can produce a "competition effect" dampening or squeezing incumbent workers' wages. Third, illegal labor can have a "complement effect" if used as an

additional input, boosting measured productivity in the short term, since reported legal labor would be unaltered.

Empirically, causal effects can be measured by the difference between the treated unit's outcome and its unobservable counterfactual, i.e., the outcome of the treated unit in the absence of the treatment. To construct the counterfactual from available data, we use the Synthetic Control Method (SCM) proposed by Abadie et al. (2010). The advantage of using the SCM is to account for unobserved time-varying heterogeneity, as agrimafias' activity and illegal labor availability. In such cases, the SCM can provide unbiased estimates of the counterfactual with more identification power than traditional regression methods (Gobillon and Magnac, 2016).

Our results point towards an increase of illegal employment on vineyards after the 2011 migration wave. Indeed, we find that this labor supply shock has a statistically significant causal effect on labor productivity and wages on southern Italian vineyards. For the Treated South, we find an average increase of labor productivity of 14% over the post-treatment period (2011 and 2012) while, regarding average hourly wages, results indicate a wage dampening effect between 7.3% and 23.8% in the same time span. Estimating separate counterfactuals for Sicily and Apulia shows that Sicily, which received most of the migrant wave, absorbed the largest part of the illegal labor after 2011. In fact, effects on labor productivity (16.4%) and wages (10.6%-25.6%) are more pronounced and statistically significant for Sicily. Given the absence of either technological, price, or additional labor market shocks in 2011/2012, our findings are likely explained by unreported employment of illegal workforce which competes with as well as partly substitutes and/or complements legal labor.

The remainder of the paper is organized as follows: Section 2 briefly summarizes background information about this study and reviews the relevant literature. Section 3 explains the SCM and outlines its advantages and disadvantages. The data are described in Section 4. Section 5 presents the results, and Section 6 concludes.

## **2 Background and Literature**

### **2.1 Agrimafias and Migrant Labor in Southern Italy**

Italy's agricultural production is 99% represented by 5,000 groups of medium and small-sized farms. In order to enable Italian agriculture to sustain the competition with foreign markets, illegal migrant labor is highly exploited with wages below legal

minimum thresholds (850 euros a month, about 5 euros per hour) and on average 40% lower than domestic wages (Joint ETI, 2015). The Italian Association for Juridical Studies on Immigration (ASGI, 2015) reported several violations of the EU Directive 2009/52/EC (EU, 2009) on illegal immigration and illegal employment of migrants without the required legal status in the EU. About 400,000 workers are estimated to be at risk of exploitation by caporalato, of which 80% are migrants (Flai-Cgil, 2014). Indeed, about a third of total agricultural employment is illegal, and up to 70% in Apulia at local level (Eurispes, 2014).

The exploitation of migrant workforce is inevitably linked to caporalato, and occurs through the intermediation of gangmasters called *caporali* who negotiate with farmers and supply migrant workers. Caporali charge fees for workers' transportation, food, phone charging and accommodation, keeping about half of a worker's daily salary. The latter consists of no more than 30 euros, with an hourly wage between 1.6 and 3 euros per hour over a 12/16-hour working day (Palmisano and Sagnet, 2016). However, for most migrants caporalato is often the only option to find a job and a residence permit in the long-run.

Sicily and Apulia are characterized by the high density of both migrant landings and agrimafias controlling farmlands' labor supply (FRONTEX, 2016; Flai-Cgil, 2016; Bandiera, 2003). Once disembarked, migrants can enter agrimafias' illegal labor channels through several mechanisms. After landing, migrants are identified and obtain first aid in temporary refugee camps called *hotspots*. However, these migrants often want reach other EU countries like Germany and Sweden (Kirgegaard, 2016), which is difficult given their initial illegal status. Thus, many of them refuse identification, leave the hotspots and, with the aim to earn money and obtain documents, may enter illegal labor and/or criminal channels (Dustman et al., 2016).<sup>3</sup> As a consequence, refugees and migrants are vulnerable to mafia organizations promising journey facilitations and (forged) documents offered in exchange for illegal labor in agriculture (EUROPOL-EMPACT, 2013, EUROPOL-EMSC, 2016).

Asylum seekers accepting identification and waiting for the acceptance of their request, which may take more than two years, enter the System for the Protection of Asylum Seekers and Refugees (SPRAR) managed by local associations. The asylum seeker status, however, prevents legal access to the labor market during most of the

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<sup>3</sup>By law, migrants without documents and asylum seekers are sent back to the EU member state which they first entered, as only the latter is responsible for assessing the asylum claim and/or the expulsion decision (Dublin Regulation, 2013). As a result, in 2015 one out of three landed migrants refused identification (Italian Court of Inquiry on Migration, 2015).

waiting time. Further, due to high rejection rates of asylum requests (around 40% in 2011 and 60% in 2016; Italian Interior Ministry, 2016), migrants again have incentives to leave the facilities, look for an illegal job, and possibly obtain a work visa through their employer. In case of a failed asylum request, rejected asylum seekers and migrants are placed in detention centers, where they wait up to 18 month for the expulsion sentence, usually in very poor sanitary and living conditions (Human Rights Watch, 2014). Again, many immigrants leave detention centers and become potential illegal labor force (MigrantSicily, 2016, Corriere delle Migrazioni, 2015). In summary, agrimafias and migrant labor in agriculture are interlaced, moved by different but reciprocal interests.

## 2.2 Literature

A vast literature on the impacts of immigration on productivity and labor market outcomes has developed (for overviews see Peri, 2016; Okkerse, 2008). These analyses are performed, e.g., for the US (e.g., Peri, 2012), the EU (e.g., Moreno-Galbis and Tritah, 2016), and also Italy (e.g., Venturini and Villosio, 2008; De Arcangelis et al., 2015). Very heterogeneous findings show both positive and negative effects on native wages, employment, and productivity (see Dustmann et al., 2016, and citations therein). However, most studies focus on the long-term consequences of immigration rather than the short-term impact of sudden migrant inflows.

Such a sharp and unexpected migrant inflow characterizes a positive labor supply shock and, as in our case, can also be seen as a quasi-natural experiment. The literature has used such settings to evaluate effects of migration waves in several countries. One of the most analyzed cases is the 1980 Mariel boatlift, a mass migration of Cubans to the US, especially to Miami, which occurred when Fidel Castro opened the boarders for a short window of time. Card (1990) was the first to study the labor market responses to this sudden migration wave and to compare the labor market outcomes in Miami and control cities. Using subgroups of the population most likely to compete with the migrants on the labor market, results indicate no effects on wages and wage dispersion in Miami. Lewis et al. (2004) argues that a major reason was the fast adaption of the local industries towards more unskilled-intensive technologies. Based on the SCM, the Mariel boatlift has been re-evaluated by Borjas (2015, 2016) and Peri and Yasenov (2015). While the former finds considerable negative wage effects for some subgroups of the workforce, the latter do not, likely due

to the use of different samples. Further, both studies estimate the counterfactual, i.e., the synthetic control unit, over a rather short time span of eight years before the treatment to predict a twelve year post-treatment period. This creates the risk to produce biased estimates (Abadie et al., 2010).

Several papers analyze the labor market impacts of the recent migration waves after the Syrian civil war start in 2011. Focusing on Turkey, Ceritoglu et al. (2015) estimate negative causal effects on employment as well as no wage effects in a Difference-In-Differences (DID) framework. Likewise, Tumen (2016), Del Carpio and Wagner (2015) and Balkan and Tumen (2016) conclude that a strong displacement of natives by immigrants occurs especially in the informal sector and, at the same time, unskilled men benefit from increasing employment opportunities. However, Peri (2016) argues that the identification of these causal effects could be biased due to potential spillovers between the neighboring Syria and Turkey, preventing potential outcomes caused by forced migration to be disentangled from other labor market adjustments. A last stream of studies is concerned with repatriation and includes a study by Hunt (1992) on emigration from Algeria to France after Algerian independence in 1962, a study by Carrington and De Lima (1996) on the repatriation from Africa towards Portugal in the 1070s, and an analysis of Russian immigration to Israel after the collapse of the Soviet Union studied by Friedberg (2001). However, although these studies also analyze sudden migration inflows, several identification problems occur, as discussed by Okkerse (2008) and Peri (2016). As Peri (2016) argues, a major problem of analyzing such repatriation inflows can be the non-exogenous distribution of immigrants in the host countries, i.e., migrants chose their destinations, leading to omitted variable bias.

### **3 Methodology**

The true causal impact of a labor supply shock on vineyards productivity and wages is given by the difference in labor market outcomes between the treated unit after the shock and its counterfactual, i.e., the outcomes of the treated unit had the shock not happened. The SCM builds upon the potential outcomes approach (Rubin, 1974) to estimate a synthetic control, i.e., the counterfactual, computing the Average Treatment effect on the Treated (ATT) as the post-shock average difference between the observed outcomes of the treated unit and the synthetic control (Abadie et al., 2010). The idea of the SCM is to weigh units in the control group (a.k.a. donor pool)

before the shock to resemble the treated unit in all outcome-relevant variables, in particular observed time-varying covariates and a set of pre-intervention outcomes. Once the donor pool is weighted to predict pre-treatment productivity and wage time trends of the treated unit, differences post-treatment would be only due to the shock if the treated unit is accurately fitted by the synthetic control pre-treatment. Formally, for  $i = 1, \dots, J + 1$  regions and  $t = 1, \dots, T$  time periods with  $1 \leq T_0 < T$  pre-treatment periods, let  $Y_{it}^N$  be the labor market outcome of the treated unit  $i$  in time  $t$ , if not exposed to the shock. Suppose only the first region,  $i = 1$ , is treated, and the other  $J$  regions not. Note that SCM assumes that the shock has no anticipated effect on the outcome in any of the  $J + 1$  regions, and no spillover effects on the  $J$  control regions after the shock (Stable Unit Value Assumption, SUTVA). Consider a  $(J \times 1)$  vector of optimal weights  $W^* = (w_2^*, \dots, w_{J+1}^*)'$  with  $w_j \geq 0$  for  $j = 2, \dots, J+1$  and  $w_2 + \dots + w_{J+1} = 1$  for  $J$  control units such that  $\hat{Y}_{1t}^N = \sum_{j=2}^{J+1} w_j^* Y_{jt}$ . The aim of this analysis is to obtain the ATT as the gap between the post-treatment outcome of the treated unit and the synthetic control (1):

$$\hat{\alpha}_{1t} = \frac{1}{T - T_0} \sum_{t > T_0} [Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}]. \quad (1)$$

The estimation of the optimal  $W^*$  follows a nested optimization procedure. First, an inner optimization minimizes the Euclidean distance between  $X_1$  and  $X_0W$ ,  $(r + k) \times 1$  and  $(r + k) \times (J)$  matrices, respectively, containing  $k$  covariates and  $r$  linear combinations of pre-treatment outcomes used as predictors (2):

$$W^* = \arg \min_W \|X_1 - X_0W\|_v = \sqrt{(X_1 - X_0W)'V(X_1 - X_0W)}, \quad (2)$$

where  $V$  is a  $(r + k) \times (r + k)$  symmetric diagonal matrix with non-negative components, in which the diagonal elements  $v = (v_1, \dots, v_{r+k})$  are predictor weights assigned to the fitted pre-intervention variables. In an outer optimization,  $V^*$  can be estimated such that the Mean Squared Error (MSE) of labor market outcomes is minimized for pre-treatment periods (3):

$$V^* = \arg \min_V (Y_1 - Y_0W^*(V))'(Y_1 - Y_0W^*(V)), \quad (3)$$

where  $Y_1$  and  $Y_0$  refer to linear combinations of pre-treatment outcomes of the treated and the untreated unit, which can be, e.g., averaged over some pre-treatment periods.

Once control unit and predictor weights are estimated according to 2 and 3, the outcome of the synthetic control, i.e., the counterfactual outcome, is computed as a weighted linear combination of untreated units' outcomes as  $\sum_{j=2}^{J+1} w_j^* Y_{jt} = \hat{Y}_{1t}^N$ . For  $t > T_0$ , the average difference between the latter and  $Y_{1t}$ , the outcome of the treated unit, is the estimated ATT in (1).

The SCM identifying assumptions are twofold. First, the outcome of all regions is required to follow a linear model, like, e.g., a factor model including interactive fixed effects that capture time-varying unobserved heterogeneity (see Abadie et al., 2010, and Ahn et al., 2013). In our setting, this assumption seems to be realistic, as wage and agricultural production functions are typically considered linear in logarithms (Bardhan, 1973; Hayami and Ruttan, 1970; Mincer, 1958). Second, there exists optimal (non-negative) weights (smaller than one) that build the synthetic control as a convex linear combination of control units matching a set of covariates and outcomes pre-treatment. As a consequence, provided that the number of pre-treatment periods is large, the synthetic control is an unbiased estimator of the counterfactual, which approximately fits the treated unit also in its individual time-varying heterogeneity (Abadie et al., 2010). As a result, the second assumption is realistically fulfilled if the first one holds, given that only data of comparable regions in terms of observed covariates and outcomes are chosen. In this way, the SCM prevents both interpolation and extrapolation biases typical of regressions (King and Zeng, 2006). In particular, Abadie et al. (2015) prove that regression weights are not limited to lying between zero and one, allowing extrapolation. In addition, note that the SCM assumes conditional independence on past outcomes, i.e., that potential outcomes are independent of the treatment conditional on a set of covariates and pre-intervention outcomes. Thereby, including past outcomes proxies for all (time-varying) unobserved confounders of the treatment causal effect.

Being this setting not suitable to large-scale (asymptotic) inferential techniques, placebo inference, a.k.a. permutation tests, is performed by building a synthetic control for each region in the donor pool, and estimating the corresponding ATT (Abadie et al., 2010). Empirical p-values are then computed as the probability to obtain ATTs as large as the treated unit's, i.e.,  $\frac{\sum_{j=2}^{J+1} \mathbf{1}(\hat{\alpha}_j \geq \hat{\alpha}_1)}{J}$ .

In addition to placebo tests, a way to test for significance of our results is to condition on the quality of the average pre-treatment fit to obtain the likelihood of an abnormal average post-treatment gap. Thus, we analyze the average post-treatment gap, i.e., the ATT, for each unit (treated and placebos) given the corresponding average pre-

intervention gap, computed as Mean Absolute Deviation (MAD). A very small MAD (large ATT) indicates a very good fit before the shock (very bad fit after the shock). Thus, we expect the treated unit to display a very large ATT in absolute terms and a low level of MAD. This is not the case in the placebos, for which ATT and MAD are expected to be similarly high (or small) if the control units are indeed untreated. Thereby, after estimating synthetic controls for every region in the donor pool, we compute the respective ATT and MAD. Formally, the ATT is expressed as  $\hat{\alpha}_i$  and the MAD as  $T_0 \sum_{i=1}^{J+1} |Y_{it} - \hat{Y}_{it}^N|$  for  $i = 1, \dots, J + 1$ , and  $\hat{Y}_{it}^N$  being the synthetic control estimated for every region  $i$ . This inferential test obtains the empirical p-values as follows:

$$\frac{\sum_{j=2}^{J+1} \mathbf{1}(ATT_j \geq ATT_1)}{J} \text{ s.t. } MAD_j \leqslant MAD_1, \quad (4)$$

for every  $j = 2, \dots, J + 1$ .

Note that this test differs from the inferential technique performed, e.g., by Abadie et al. (2010), who compute the ratio between post-intervention and pre-intervention MSE. In this case, the numerator results to be inflated in the presence of, e.g., a large treatment effects in one single post-intervention period, as squaring post-intervention gaps assigns a higher weight to exceptionally large deviations. On the contrary, a counterweight of this effect with similar effects in the denominator for pre-intervention MSE is unlikely to occur as every placebo unit with a much (typically, three times) higher MSE than the one of the treated unit is excluded from the computation of the p-values. Motivated by the above, our measure is preferred as it seems to have more power.

In conclusion, the SCM allows for a multidimensional unobserved heterogeneity, i.e., for multiple interactive effects, not just additive ones as imposed, e.g., in the DID setting (Gobillon and Magnac, 2016). In practice, interactive effects can be considered time-variant fixed effects – like, for example, region-specific variations in organized crime activities. Therefore, the SCM generalizes the DID method allowing to clearly identify the causal effect of migrant labor supply shock on productivity and wages, disentangling the ATT from all other unobserved time-varying confounding factors present at cross-sectional level.

## 4 Data

We use data from the Farm Accountancy Data Network (FADN, European Commission, 2017) and explanatory variables from the Eurostat labor force survey (LFS, EUROSTAT, 2017). The data has a panel structure from 1991 to 2012. Each cross-section is a region on *NUTS 2* level, and contains values representing the average farm of each regions. Average farms are representative due to stratified sampling and weighting. These farms are vineyards, i.e., specialized in grape and wine production.<sup>4</sup> The sample consists of 25 regions of which 14 are located in Italy and 11 in France, adding up to 525 observations.<sup>5</sup> These regions are comparable for several reasons. First, France and Italy share a border, a similar political and economic system as they are both EU members, and have similar climatic conditions (from warm Mediterranean in the South to temperate oceanic climate in the North). Finally, both countries have a long vitivinicultural tradition.

As a treated unit, we build a weighted average of Sicily and Apulia called the *Treated South*, with weights given by the number of vineyards in the two regions. As a robustness check, we also analyze the two regions separately.<sup>6</sup> The treatment, i.e., the migration wave, takes place in 2011, especially in the months preceding the 2011 grape harvest (see Figure 1). Further, as reported by the local governments (Press Regione Puglia, 2011), a high share of young migrants escape refugee camps and detention centers (e.g., 93% in Apulia).

Despite data availability until 2013, we restrict the post-treatment analysis to 2011 and 2012. The reasons are twofold. First, the effect of the treatment could be confounded by the additional landings registered in Sicily in 2013 (see Figure 1 and FRONTEX, 2016). Second, potential spillover effects from 2013 onwards may violate the assumption on the untreated status of the control regions (SUTVA). In fact, 2011 landed migrants who do not immediately flee from the hotspots in Sicily and Apulia are distributed among facilities all over Italy. At the earliest in 2013, immigrants receive their expulsion or asylum decision, after which they may escape or leave these facilities. At this point, they might also enter illegal labor channels

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<sup>4</sup>Additional farm income from other agricultural activities plays a minor role, and it only amounts to 3.5% on average, with very low variation across regions and time.

<sup>5</sup>This selection excludes non-winegrowing regions. For six regions single missing data points until 2003 are imputed using Multivariate Imputation by Chained Equations (MICE, see Buuren and Groothuis-Oudshoorn, 2011). Few extreme observations are also handled with transformation.

<sup>6</sup>We exclude Calabria due to limited data availability. Yet, Calabria accounts for less than 1% of total wine production in Italy.

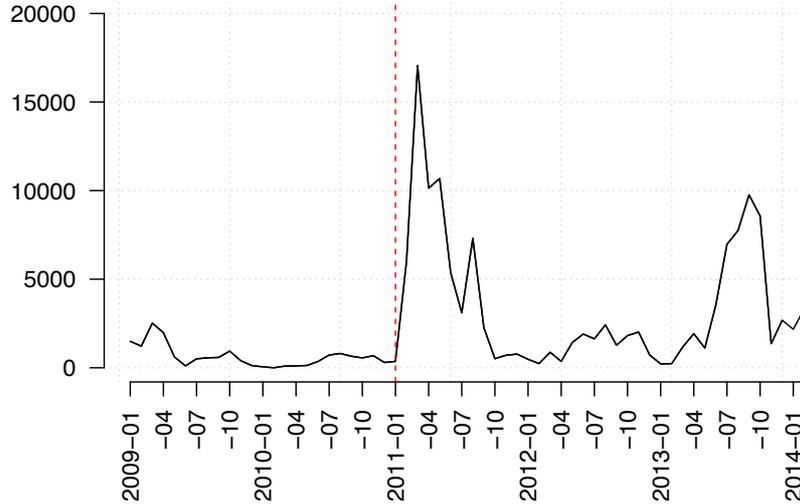


Figure 1: Boarder crossings to Italy via the central Mediterranean route (Own illustration, source: FRONTEX (2016))

(Giangrande, 2017), causing a violation of SUTVA.

To analyze labor productivity, we define our logged dependent variable *LabProd* as the total output from crops in euros divided by total hours worked, which is the sum of all paid and unpaid hours worked. It should be noted that this measure may vary due to quantity and price variations, the latter being the main source of concern. However, we are confident to rule out such effects for several reasons. First, price effects could be sizable for high-quality wines, i.e., those with Protected Designation of Origin (PDO). In 2011, Sicilian (Apulian) PDOs account for only 4% (15%) of the regional wine production, and 1% (6%) of the Italian PDOs' production (Baccaglio, 2016a). Thus, price fluctuations can have limited impact overall. Second, no sizable price shocks among Sicilian and Apulian PDOs has been registered. Third, although we observe price variations for single PDOs, average prices are similarly trended in all regions (Baccaglio, 2016b). The only exception is Veneto that experienced the Prosecco-boom with a price and sales increase by around 50% between 2009 and 2012.

To construct a synthetic unit, we use explanatory variables containing measures for capital, land, labor, and other farm and labor market characteristics. Regarding capital, we match upon two measures: the share of operating expenditures for machinery

and buildings over total expenditures, and a measure of capital intensity expressed as book values of machinery over total agricultural income. Land productivity is included in terms of harvested wine per hectare, divided by total hours worked. This land productivity measure also controls for environmental factors and operational characteristics such as weather conditions. To control for different degrees of diversification at farm level, we use the share of total costs covered by income from wine. To control for labor market characteristics, we include the unskilled workforce defined as the share of the population above the age of 15 with less than primary or secondary education (ISCED11), and the regional unemployment rate. Lastly, following the literature (Abadie et al., 2010), we also match upon linear combinations of lagged values of the dependent variable.

To analyze effects on wages, we construct the logged dependent variable *Wage* as the average hourly wage. The latter is the farm's total wage bill divided by paid hours worked. As explanatory variables, we use all the covariates described above, *LabProd*, and additional wage determinants to account for the input mix of unpaid and paid hours. Therefore, we include the ratio of unpaid hours multiplied by the average wage over total wage, and the share of unpaid hours of total hours worked. The boxplots in Figure 2 show the descriptive statistics of the variables averaged over the observation period. For comparability and visualization reasons, each variable is normalized to unity by mean correction. The figure shows that all variable values for Sicily, Apulia and the Treated South are within the range of the whole dataset, and mostly around the sample mean. Further, we observe a considerable variance reduction for the Treated South. This softens the impact of abnormal observations due, e.g., to weather shocks, and guarantees common support for the SCM. Regarding our dependent variables, we observe that both are between the first and the second quartile of the sample, with common support.

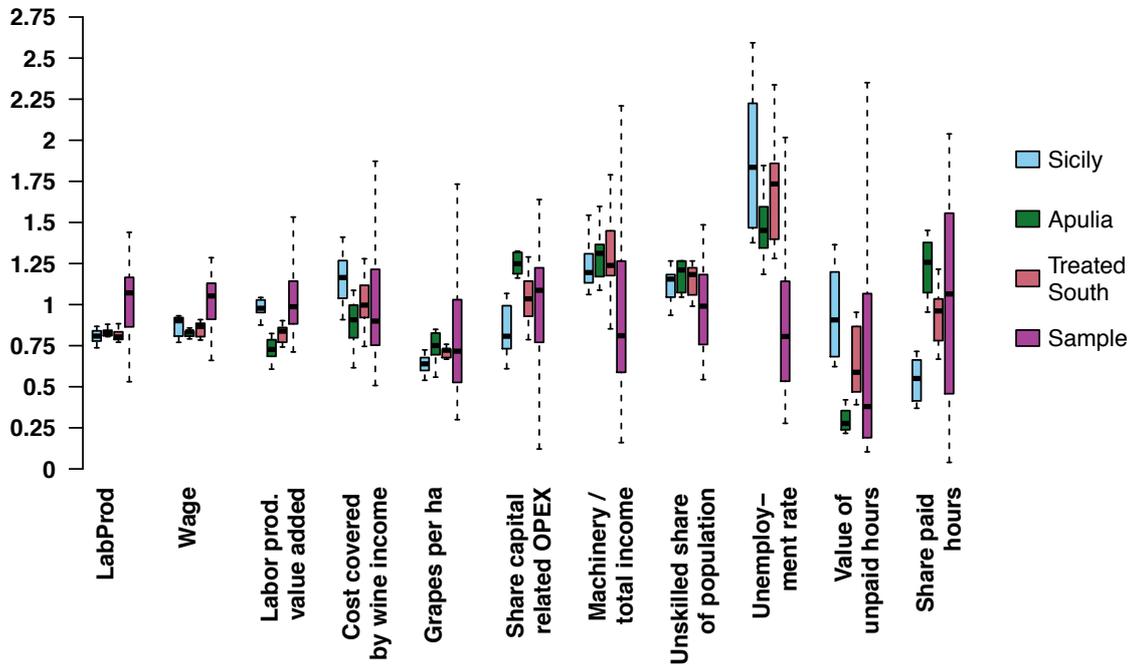


Figure 2: Descriptive statistics: Boxplots of mean-corrected variables

## 5 Results

To identify potential illegal employment on vineyards in southern Italy of the 2011 migrant wave, we estimate the causal effects of the latter on labor productivity and wages. The estimates indicate a statistically significant positive effect of around 14% on labor productivity. Average hourly wages, on the contrary, are 7.3% to 23.8% lower than those predicted by the estimator. Separate analyses for Sicily and Apulia show causal effects of the same estimated sign and of similar magnitudes. However, these effects are more pronounced and statistically significant for Sicily. This implies that the results for the Treated South are mainly driven by the latter. Therefore, the region absorbing most of the 2011 migration wave also experiences stronger causal impacts on labor productivity and wages.

### 5.1 Analysis: Treated South

First, we implement the SCM to build the counterfactual for the Treated South. Tables 1 and 2 show the corresponding outcome predictor means for the Treated

South, its synthetic counterpart, and the donor pool. It can be seen that the SCM builds a very similar synthetic unit in all predictors, resembling the treated unit better than the sample mean of the control regions for nearly all variables.

	Treated	Synthetic	Sample Mean
LabProd	2.331	2.341	2.887
Unskilled share of population	0.185	0.184	0.161
Unemployment rate	0.159	0.086	0.079
Labor productivity value added	3.159	4.101	3.986
Cost covered by wine income	1.490	1.498	1.483
Grapes per ha	2.167	2.113	3.537
Share of capital-related OPEX	0.052	0.052	0.058
Machinery / total income	0.627	0.626	0.454

Table 1: LabProd - Predictor means for the Treated South

	Treated	Synthetic	Sample Mean
Wage	1.766	1.744	2.122
LabProd	2.286	2.351	2.832
Unskilled share of population	0.185	0.191	0.161
Unemployment rate	0.159	0.128	0.079
Cost covered by wine income	1.658	1.795	1.559
Labor productivity value added	3.159	3.496	3.986
Grapes per ha	2.267	1.725	3.567
Share of capital-related OPEX	0.048	0.036	0.056
Share of paid hours	0.285	0.266	0.311
Value of unpaid hours	2.767	3.607	3.808
Machinery / total income	0.609	0.477	0.442

Table 2: Wage - Predictor means for the Treated South

Figures 3 and 4 show the paths of LabProd and Wage ( $y$ -axis) for the Treated South (black line) and its synthetic counterpart (dotted line) for the observation period ( $x$ -axis). Both plots indicate a good pre-treatment fit, i.e., the weighted synthetic unit captures the development of the observed data. Yet, both plots also display a gap between observed data and the synthetic unit after the migration wave.

For LabProd, post-treatment gaps between the treated unit's path and its counterfactual suggest an increase of LabProd caused by the migrant inflow. The gaps are of considerable magnitude, with an average of 14% for 2011 and 2012.

For Wage, we observe a very flat development in the post-treatment period. The synthetic Wage, however, increases considerably after 2010, indicating that the variable should have increased conditional on our covariates. Given that the synthetic unit very well resembles the Treated South in the pre-treatment period, we interpret this as a causal effect of the migration inflow on wages. The overall gap in the post-treatment period amounts to on average 23.8%, indicating a considerable wage dampening. However, an initial gap in 2010 is visible (see Figure 4). We can adjust for this misfit by subtracting the latter from the post-treatment gaps. Again, a wage dampening of on average 7.3% in the post-treatment period is present.

The quality of the matching can be assessed looking at the outer optimization error, i.e., the MSE. A very small MSE indicates very good pre-treatment fit, as it is the case here (0.009 and 0.008 for LabProd and Wage, respectively). The treated units' counterfactuals are based on estimated weights for each control region displayed in Table 3. To construct the counterfactual for LabProd, six Italian and two French regions are used from the donor pool, whereas Abruzzo, a region also in southern Italy, obtains the highest weight. To build the synthetic Wage, only three units are used overall. The southern Italian regions Molise and Sardinia obtain large weights, and the French Midi-Pyrénées contributes to a smaller extent.

Figure 3: Top: LabProd of Treated South (solid) vs synthetic unit (dotted)  
Bottom: LabProd of Treated South (black) vs placebos (gray)

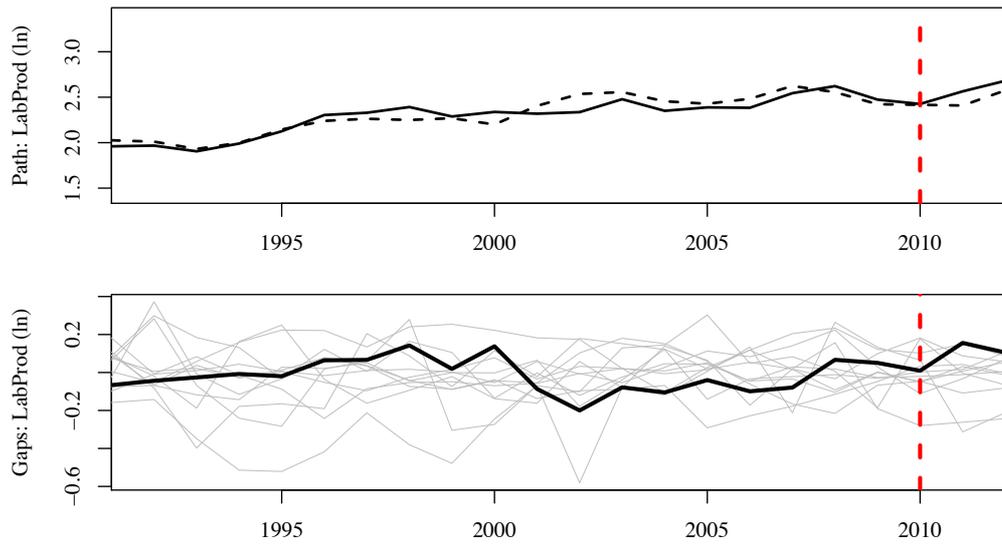
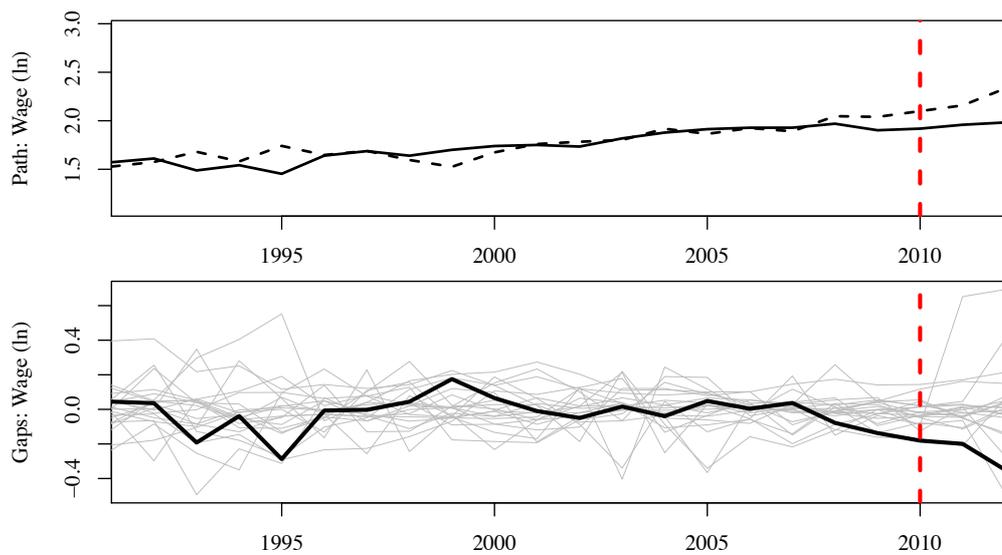


Figure 4: Top: Wage of Treated South (solid) vs synthetic unit (dotted)  
Bottom: Wage of Treated South (black) vs placebos (gray)



Control Units	Prod.	Wage	Control Units	Prod.	Wage
Abruzzo	0.318	0	Midi-Pyrénées	0	0.078
Alsace	0	0	Molise	0	0.466
Aquitaine	0	0	Pays de la Loire	0	0
Bourgogne-Franche-Comté	0	0	Piedmont	0	0
Campania	0	0	Poitou-Charentes	0	0
Centre-Val de Loire	0	0	Provence-Alpes-Côte d’Azur	0	0
Champagne-Ardenne	0.007	0	Rhône-Alpes	0	0
Emilia-Romagna	0.171	0	Sardinia	0.200	0.454
Friuli-Venezia Giulia	0	0	Trentino-South Tyrol	0	0
Languedoc-Roussillon	0.136	0	Tuscany	0.019	0
Lombardy	0	0	Veneto	0.040	0
Marche	0.108	0			

Table 3: Estimated weights to build the synthetic Treated South

To test statistical significance of our estimates, we conduct permutation inference performing placebo tests à la Abadie et al. (2010). Therefore, we estimate the causal effects of a potential ATT over 2011 and 2012 for every region in the donor pool using the SCM. Thereby, we exclude Sicily, Apulia and the Treated South from the donor pool. This ensures that the placebos’ synthetic control units are not influenced in the post-treatment period by the actual treatment. To limit the impact of units with a very bad fit, all regions with a pre-treatment MSE five times higher than the one obtained for the Treated South are dropped.

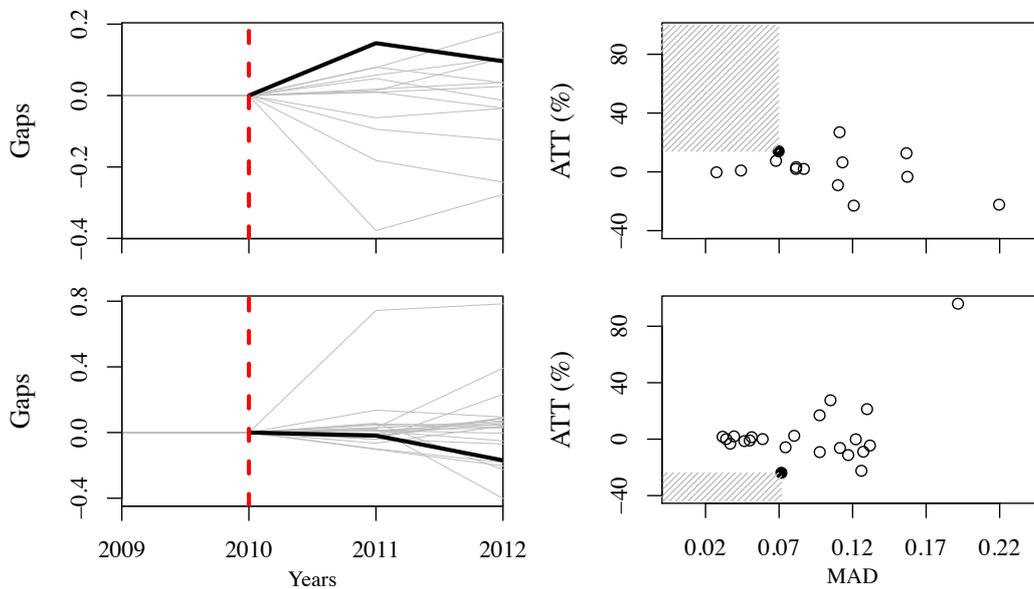
The lower plots of Figures 3 and 4 show the gaps between the actual path and its synthetic counterpart for the Treated South (black line) and for each placebo (gray lines). The LabProd average post-treatment gap (Figure 3) for the Treated South is positive contrary to most placebo gaps, and no placebo shows similar deviations. Overall, the positive effect on LabProd is statistically significant with a p-value of 1/13, i.e., about 8%.<sup>7</sup> With respect to Wage (Figure 4), results show a large negative gap for the Treated South compared to all the placebos (gray lines). Indeed, the 23.8% average decrease in Wage is the second largest in absolute terms over the other 22 placebo estimates, leading to significance at the 9% level.

To further assess the significance of our estimates, additional inferential analysis is

<sup>7</sup>We exclude Veneto in this representation, as the strong price effect of the Prosecco-boom induces a strong upward trend of LabProd already from 2009 onwards.

performed by means of two tests. Contrary to the previous standard placebos, these tests condition on the quality of the pre-treatment fit to obtain the likelihood of abnormal post-treatment gaps. First, we correct post-treatment gaps for each region (treated and placebos) by subtracting the corresponding gap in 2010 (see Figure 5, left). Second, we condition average post-treatment gaps (ATTs) on the overall goodness of fit in the pre-treatment period in terms of MAD (see Figure 5, right). The left column of Figure 5 shows abnormal post-intervention gaps for LabProd in the Treated South. Yet, the adjusted Wage effect of 7.3% is less abnormal, and we may find a comparable effect in other regions if assigned to treatment. However, it has to be noted that this test only corrects for the potential 2010 gap. Instead, when accounting for the average quality of fit of the whole pre-treatment period (Figure 5, right), results highlight the abnormality of the identified ATTs for both LabProd and Wage. Indeed, no placebo has a higher ATT given the MAD of the Treated South, i.e., no placebo is in the shaded area. Contrary to the test above, the wage dampening effect shows significance at the 5% level, and LabProd at the 7% level (1/14, Veneto here included).

Figure 5: LabProd (top) and Wage (bottom) of Treated South – 2010-adjusted treatment effects (left) and ATT / pre-intervention MAD (right)

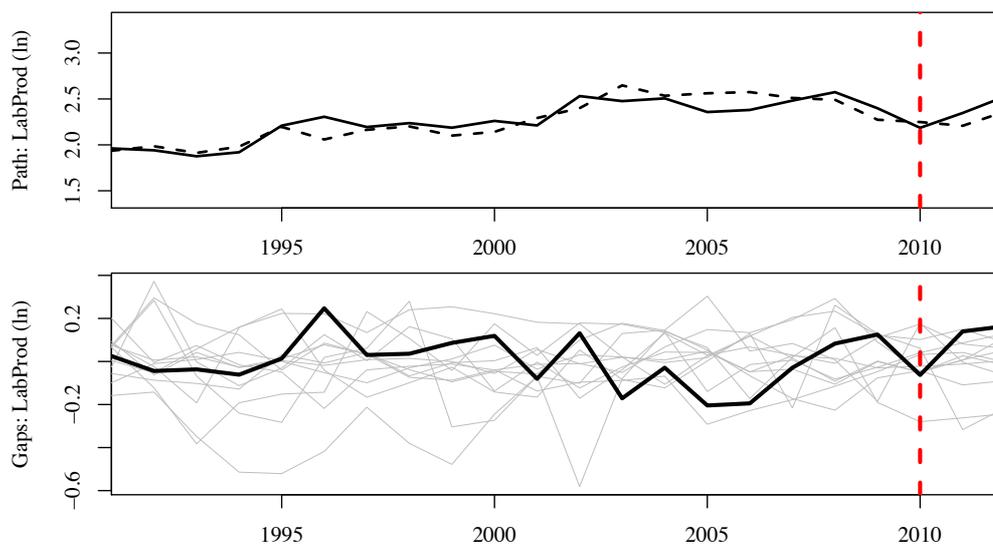


## 5.2 Analysis: Sicily

As a robustness check, and to better understand the drivers of the results presented above, we perform separate treatment effect estimations for Sicily and Apulia. As both regions are treated according to our assumptions, Apulia is excluded from the donor pool for Sicily, and vice versa.<sup>8</sup> The model specifications, the estimation and inferential techniques are identical to the ones used for the Treated South.

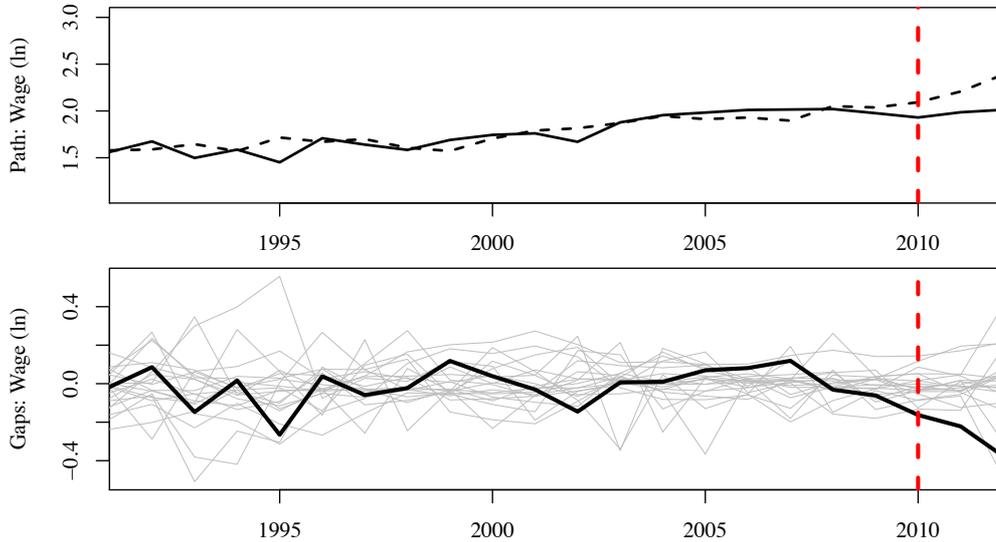
Figure 6 shows path and placebos for Sicily. The plots show a similar fit to the one of the Treated South, both visually and in terms of MSE. Between 2003 and 2007, two years characterized by heat waves and bad harvests, the quality of the fit slightly deteriorates, but it is optimal close to the treatment period.

Figure 6: Top: LabProd of Sicily (solid) vs synthetic unit (dotted)  
Bottom: LabProd of Sicily (black) vs placebos (gray)



<sup>8</sup>For the purpose of conciseness, detailed results are only presented for Sicily. For Apulia, the corresponding figures of the analysis can be found in the Appendix.

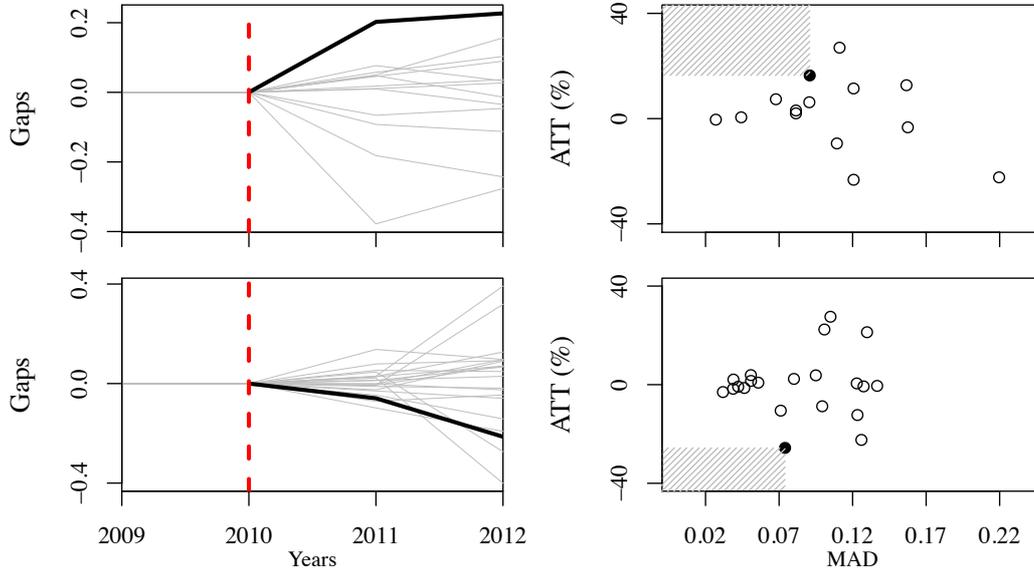
Figure 7: Top: Wage of Sicily (solid) vs synthetic unit (dotted)  
 Bottom: Wage of Sicily (black) vs placebos (gray)



The ATT for LabProd in 2011/2012 amounts to 16.4%, thus it is higher than the effect estimated for the Treated South. For Wage, we find that observed wages are on average 25.6% lower than predicted, again a stronger effect than for the Treated South. Subtracting the existing gap in 2010 still indicates wage dampening of 10.6%. Using placebo inference, we find a significant effect on LabProd at 8% significance level (p-value of 1/13, see Figure 6). Likewise for the Wage, placebos indicate an abnormal treatment effect for Sicily with significance at 5% level (p-value of 1/21, see Figure 7).

Additional inference is presented in Figure 8. In the graphs on the left, post-treatment gaps corrected by the corresponding 2010 gaps show an outstanding ATT for LabProd with a significance level of 8% (1/13) as before. Similar to the Treated South, the 2010-adjusted ATT for Wage is not outstanding if compared to some other placebos, suggesting low statistical significance. In the graphs on the right, conditioning on Sicily's MAD – thus on the average gap over the whole pre-treatment period – proves instead that there is no placebo with a treatment effect as strong as the one for Sicily given the quality of the pre-treatment fit. Thus, we conclude that the 2011 migration wave had an abnormally strong causal effect on labor productivity and wages on Sicilian vineyards.

Figure 8: LabProd (top) and Wage (bottom) of Sicily – 2010-adjusted treatment effects (left) and ATT / pre-intervention MAD (right)



Comparing these results with those for Apulia, we observe very similar effects on both LabProd and Wage, although of lower statistical significance. In particular, the effects on LabProd and Wage are more pronounced and statistically significant for Sicily, which implies that the results for the Treated South are mainly driven by the latter. Therefore, the region absorbing most of the 2011 migration wave also experiences stronger causal impacts on labor productivity and wages.

## 6 Conclusions

Up to 500,000 immigrant workers are irregularly employed in the Italian agricultural sector (Flai-Cgil, 2014), especially in southern Italy where the availability of illegal workforce is systematically increased by migrant inflows irregularly entering the EU via the Mediterranean. Most of these illegal agricultural workers are estimated to be at risk of exploitation by caporalato, a system of illegal supply and mistreatment of underpaid workers (Flai-Cgil, 2014).

We aim at identifying illegal employment on vineyards in southern Italy after the 2011 migration wave. For this purpose, we test for causal effects of this large and unexpected labor supply shock on labor productivity and wages in Sicily and Apulia,

the recipients of the shock. We use a representative sample of farm-level data aggregated at regional level between 1991 and 2012. We estimate causal impacts on Sicily, Apulia and the Treated South, a weighted average of the two. Using the synthetic control method allows us to account for time-varying and unit-specific unobserved heterogeneity such as, e.g., agrimafias activity and illegal labor availability.

Our results show that the 2011 migrant wave caused a statistically significant increase of labor productivity of 14% on average over 2011 and 2012. On the contrary, a significant negative wage effect between 7.3% and 23.8% is found over the same time span. Yet, data does not indicate a decrease in wages, but rather a dampening effect such that wages would have followed an increasing path after 2011 had the shock not taken place. Further, both causal effects are of the same estimated sign for all treated units. However, causal estimates for Sicily are the strongest in terms of magnitude and statistical significance, and therefore drive the findings for the Treated South.

Given the absence of either technological, price, or additional labor market shocks in 2011/2012, we conclude that both the increase in measured labor productivity and the wage dampening are likely caused by the employment of illegal workforce on vineyards after the 2011 migration wave. A displacement and/or a complement effect between legal and illegal labor, and a competition effect among the agricultural workforce are possible explanations. Additionally, these findings suggest that agrimafias immediately responded to the labor supply shock matching the needs of irregular migrants looking for documents with those of vinegrowers facing an increasing competitive pressure.

These results are in line with the literature (see Dustmann et al., 2016; Peri, 2016), which finds low-skilled jobs the most vulnerable to migrant labor supply shocks. Indeed, this is the case for vineyard labor: The seasonal nature and the low skill requirements of field picker jobs limit workers' bargaining power and make them extremely substitutable. In turn, an even lower bargaining power and a larger supply of field pickers keep vineyard wages close to the minimum after the shock. Further, the skill homogeneity also leads to low variation in wages. As a result, replacing legal with illegal workers – which would occur first for the least productive with the lowest wages – does not increase the average wage of the remaining legal workforce (see Del Carpio and Wagner, 2015; Tumen, 2016). For these reasons, wages on southern Italian vineyards stay close to the minimum level after the 2011 labor supply shock. Several questions remain open and should be addressed in future research. First, to better understand the impacts of migrant illegal employment on domestic agricultural

workers, displacement and complement effects among legal and illegal workforce need to be disentangled. Second, to understand the overall impact of the 2011 migration wave on labor market outcomes, the current analysis should be extended to the whole agribusiness as it is the sector that absorbs most of the illegal workforce. Third, long-term effects of the newest migration waves on labor markets need to be evaluated taking into account the current EU immigration policy and the recent regulatory efforts against labor exploitation.

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## References

- Abadie, A., Diamond, A., Hainmueller, J., 2010. Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association* 105, 493–505.
- Abadie, A., Diamond, A., Hainmueller, J., 2015. Comparative politics and the synthetic control method. *American Journal of Political Science* 59 (2), 495–510.
- Ahn, S., Lee, Y., Schmidt, P., 2013. Panel data models with multiple time-varying individual effects. *Journal of Econometrics* 174 (1), 1–14.
- ASGI, 2015. Infractions identified by the Italian Association for Juridical Studies on Immigration (ASGI) on sanctions against employers of illegally staying third-country nationals.
- Baccaglio, M., 2016a. Produzione di vino e superfici vitate - aggiornamento 2011. URL <http://www.inumeridelvino.it/2012/07/sicilia-produzione-di-vino-e-superfici-vitate-aggiornamento-2011.html>

- Baccaglio, M., 2016b. Produzione doc e docg per denominazione - dati 2014.  
URL <http://www.inumeridelvino.it/2016/06/produzione-doc-e-docg-per-denominazione-dati-2014.html>
- Balkan, B., Tumen, S., 2016. Immigration and prices: Quasi-experimental evidence from Syrian refugees in Turkey. *Journal of Population Economics* 29 (3), 657–686.
- Bandiera, O., 2003. Land Reform, the Market for Protection, and the Origins of the Sicilian Mafia: Theory and Evidence. *The Journal of Law, Economics, and Organization* 19 (1), 218.
- Bardhan, P. K., 1973. Size, productivity, and returns to scale: An analysis of farm-level data in Indian agriculture. *Journal of Political Economy* 81 (6), 1370–1386.
- Borjas, G. J., 2015. The wage impact of the Marielitos: A reappraisal. *National Bureau of Economic Research* 21588.
- Borjas, G. J., 2016. The wage impact of the Marielitos: Additional evidence. *National Bureau of Economic Research* 21850.
- Buuren, S., Groothuis-Oudshoorn, K., 2011. mice: Multivariate imputation by chained equations in R. *Journal of statistical software* 45 (3).
- Card, D., 1990. The impact of the Mariel boatlift on the Miami labor market. *ILR Review* 43 (2), 245–257.
- Carrington, W. J., De Lima, P. J., 1996. The impact of 1970s repatriates from Africa on the Portuguese labor market. *ILR Review* 49 (2), 330–347.
- Ceritoglu, E., Yunculer, G., Burcu, H., Torun, H., Tumen, S., 2015. The impact of Syrian refugees on natives' labor market outcomes in Turkey: Evidence from a quasi-experimental design. *IZA Discussion Paper* 9348.
- CMO, 2008. Regulation for Common Market Organization 479/2008. European Common Organization of Agricultural Markets (CMO).
- Corriere delle Migrazioni, 2015. Non CIE piú nessuno (7 march 2015).  
URL <http://www.corrieredellemigrazioni.it/2015/03/07/non-cie-nessuno/>

- De Arcangelis, G., Di Porto, E., Santoni, G., 2015. Immigration and manufacturing in Italy: evidence from the 2000s. *Economia e Politica Industriale* 42 (2), 163–187.
- Del Carpio, X. V., Wagner, M. C., 2015. The impact of Syrian refugees on the Turkish labor market. World Bank Policy Research Working Paper 7402.
- Dublin Regulation, 2013. Regulation no 604/2013 of the European Parliament and of the Council of 26 June 2013 establishing the criteria and mechanisms for determining the Member State responsible for examining an application for international protection lodged in one of the Member States by a third-country national or a stateless person. Official Journal of the European Union of 29 June 2013.
- Dustman, C., Fasani, F., Frattini, T., Minale, L., Schönberg, U., 2016. On the economics and politics of refugee migration. CReAM Discussion Paper Series 1616, Centre for Research and Analysis of Migration, University College London.
- Dustmann, C., Schönberg, U., Stuhler, J., November 2016. The impact of immigration: Why do studies reach such different results? *Journal of Economic Perspectives* 30 (4), 31–56.
- EU, 2009. Directive 2009/52/EC of the European Parliament and of the Council. Official Journal of the European Union of 18 June 2009.
- Eurispes, 2014. Eurispes media report 2014.
- European Commission, 2017. Farm accountancy data network.  
URL <http://ec.europa.eu/agriculture/rica/index.cfm>
- EUROPOL-EMPACT, 2013. Facilitation of illegal migration. EU Policy Cycle - EMPACT (European Multidisciplinary Platform Against Criminal Threats).  
URL <http://www.europol.europa.eu/crime-areas-and-trends/crime-areas/facilitation-of-illegal-immigration>
- EUROPOL-EMSC, 2016. Tackling the organised criminal groups profiting from migrant smuggling. European Migrant Smuggling Centre (EMSC).  
URL <http://www.europol.europa.eu/about-europol/european-migrant-smuggling-centre-emsc>

- EUROSTAT, 2017. Labor force survey. Tech. rep., Eurostat.  
URL <http://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey>
- Flai-Cgil, 2014. Agromafias and Caporalato, Second Report. Osservatorio Placido Rizzotto Flai-Cgil.
- Flai-Cgil, 2016. Agromafias and Caporalato, Third Report. Osservatorio Placido Rizzotto Flai-Cgil.
- Friedberg, R. M., 2001. The impact of mass migration on the Israeli labor market. *The Quarterly Journal of Economics* 116 (4), 1373–1408.
- FRONTEX, 2016. Migratory routes map. European Border and Coast Guard Agency.  
URL <http://frontex.europa.eu/trends-and-routes>
- Gaeta, D., Corsinovi, P., 2014. Economics, Governance, and Politics in the Wine Market: European Union Developments. Palgrave Macmillan US.
- Giangrande, A., 2017. Caporalato Ipocrisia e Speculazione. Vol. Vol. 165. *L'Italia del Trucco, l'Italia che siamo*.
- Gobillon, L., Magnac, T., 2016. Regional policy evaluation: Interactive fixed effects and synthetic controls. *The Review of Economics and Statistics* 98 (3), 535–551.
- Hayami, Y., Ruttan, V. W., 1970. Agricultural productivity differences among countries. *American Economic Association* 60 (5), 895–911.
- Human Rights Watch, 2014. Universal periodic review - italy, march 2014. Tech. rep., Human Rights Watch.
- Hunt, J., 1992. The impact of the 1962 repatriates from Algeria on the French labor market. *ILR Review* 45 (3), 556–572.
- Italian Court of Inquiry on Migration, 2015. Scientific police report on migrants' reception and identification, and on reception facilities for asylum-seekers and expulsion of illegal migrants (audition of 15 september 2015). *Bulletin of Parliamentary Councils and Commissions*, 106.  
URL <http://documenti.camera.it/leg17/resoconti/commissioni/bollettini/html/2015/09/10/69/comunic.htm>

- Italian Interior Ministry, 2016. Asylum statistics 1990-2016. Commissione nazionale per il diritto di asilo.
- Italian Penal Code, 2009. Law n. 94/2009 item 10bis on Dispositions on public security: Entry and illegal stay in the State territory (15 July 2009). *Gazzetta Ufficiale* n. 170 of 24 July 2009.
- Italian Penal Code, 2016. Law n. 199/2016 of the Penal Code against illegal labor and labor exploitation in agriculture (in effect on November 4, 2016). *Gazzetta Ufficiale* n.257 of 3 November 2016.
- Joint ETI, 2015. Decent work in italian agriculture: Counteracting exploitation of migrant workers in tomato production. Project of Ethical Trading Initiative Norway (IEH), Ethical Trading Initiative (ETI) and Danish Ethical Trading Initiative (DIEH).
- King, G., Zeng, L., 2006. The dangers of extreme counterfactuals. *Political Analysis* 14 (2), 131–159.
- Kirgegaard, J. F., 2016. How europe will fail to address the migration crisis in early 2016. VoxEU.org on 25 January.  
URL <http://voxeu.org/article/europe-s-migration-crisis-2016>
- Lewis, E., et al., 2004. How did the Miami labor market absorb the Mariel immigrants? Federal Reserve Bank of Philadelphia Philadelphia Working Papers 04-3.
- MigrantSicily, 2016. Drawn-out Landing Operations and Facilities in Free-fall: The Failure of the Italian System Creates Violence and Exploitation. *Migrant Sicily Newsletter*, September 2016.  
URL <http://migrantsicily.blogspot.de/2016/10/migrant-sicily-newsletter-september-2016.html>
- Mincer, J., 1958. Investment in human capital and personal income distribution. *Journal of Political Economy* 66 (4), 281?302.
- Moreno-Galbis, E., Tritah, A., 2016. The effects of immigration in frictional labor markets: Theory and empirical evidence from EU countries. *European Economic Review* 84, 76–98.

- Okkerse, L., 2008. How to measure labour market effects of immigration: A review. *Journal of Economic Surveys* 22 (1), 1–30.
- Palmisano, L., Sagnet, Y., 2016. *Ghetto Italia. I braccianti stranieri tra capolarato e sfruttamento*. Fandango Editore.
- Peri, G., 2012. The effect of immigration on productivity: Evidence from U.S. states. *The Review of Economics and Statistics* 94 (1), 348–358.
- Peri, G., 2016. Immigrants, productivity, and labor markets. *Journal of Economic Perspectives* 30 (4), 3–30.
- Peri, G., Yasenov, V., 2015. The labor market effects of a refugee wave: Synthetic control method meets the Mariel boatlift. National Bureau of Economic Research 21801.
- Press Regione Puglia, 2011. *Minori migranti non accompagnati: firma di un accordo con Save the Children*. Press Release, 16 February 2011.  
URL <http://www.regione.puglia.it/index.php?page=pressregione&id=9809&opz=display>
- Rubin, D., 1974. Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology* 5 (5), 688–701.
- Tumen, S., 2016. The economic impact of Syrian refugees on host countries: Quasi-experimental evidence from Turkey. *American Economic Review* 106, 456–60.
- Venturini, A., Villosio, C., 2008. Labour-market assimilation of foreign workers in Italy. *Oxford Review of Economic Policy* 24 (3), 517–541.

# A Appendix

## A.1 Results: Apulia

Figure 9: Top: LabProd of Apulia (solid) vs synthetic unit (dotted)  
Bottom: LabProd of Apulia (black) vs placebos (gray)

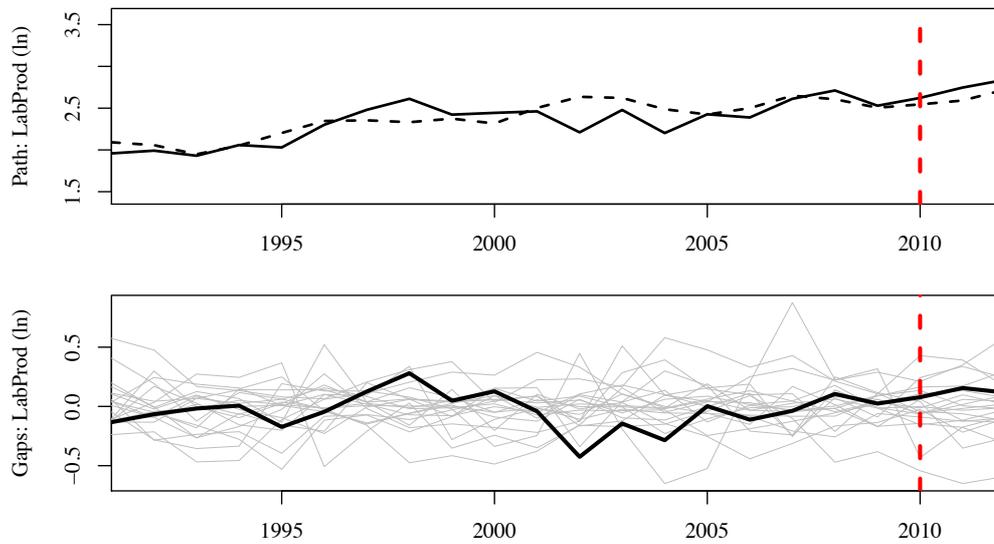


Figure 10: Top: Wage of Apulia (solid) vs synthetic unit (dotted)  
 Bottom: Wage of Apulia (black) vs placebos (gray)

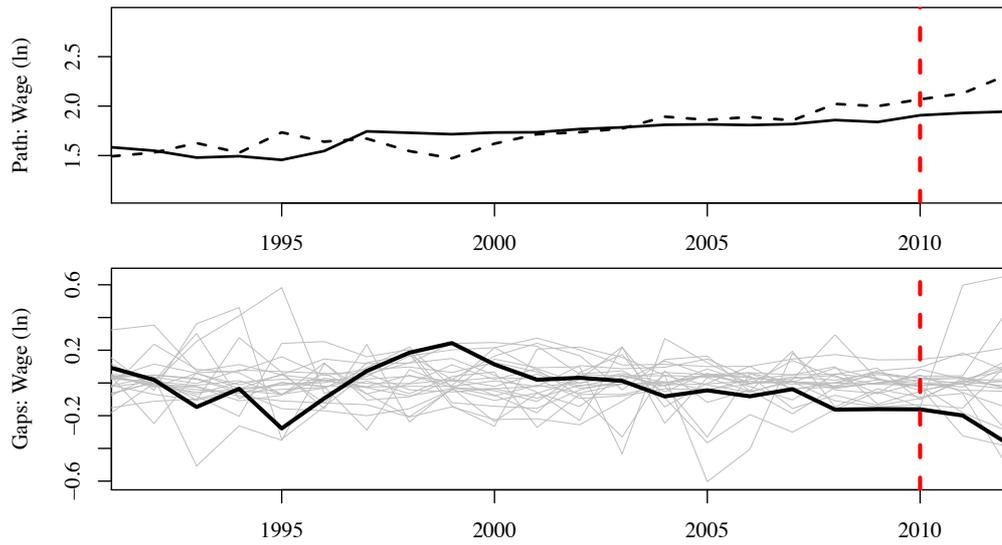


Figure 11: LabProd (top) and Wage (bottom) – 2010-adjusted treatment effects (left) and ATT / pre-intervention MAD (right)

